RESEARCH TITLE

INTELLIGENT NEUTRAL SECTION FAULT MONITORING SYSTEM ON THE COAL LINE RAIL NETWORK

by

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DECLARATION

I declare that “Intelligent Neutral Section Fault Monitoring System on the Coal Line Rail Network” is my own work and this work is submitted for the degree of Magister of Philosophiae at the University of Johannesburg.

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SIGNATURE DATE

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ABSTRACT

This research project aims to investigate a cost-effective and efficient fault monitoring that detect, diagnose and classify events arising from the neutral section assembly of a 25kV single-phase electrified railway line network. Condition monitoring and fault detection on the railways is vital, particularly on detecting faults from the state of origin to provide an accurate root cause analysis, whilst predicting inevitable failures. A concept encompassing wireless sensors and machine learning techniques is developed to detect, diagnose and predict failures resulting from a poor contact wire and pantograph interaction through cloud processing. The literature explores the advantage of employing wireless sensor networks against hard-wiring over the long stretch of the overhead wires. The clustering, prediction of tasks using machine learning techniques from the enormous volume of sensed data onsite is simplified. The fault detection and diagnosis of this experiment is conducted simultaneously through cloud processing, employing ThingSpeak™. Once data is generated and stored to the cloud, three evaluation techniques are utilised to determine the optimal number of clusters and the degree of separation. The framework is developed to detect pantograph vibrations and classify the locomotives by differentiating the events that are-non traction related from the pantograph vibrations, both k-means and support vector machine are employed to achieve the study objectives. The system triggers alarm when the set limits are exceeded. Notifications are forwarded to maintenance personnel to react during the incident. The intelligent fault monitoring system on the rail network will assists engineers and researchers in autonomous train operation and infrastructure condition monitoring.

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LIST OF PUBLICATIONS

The author contributed to the following list of peer-reviewed publication rendered during the thesis.

1. K. M. Phala, W. Doorsamy, and B. S. Paul, "A study into intelligent neutral section fault monitoring system on the coal line using wireless sensors networks," *Proceedings of the International Heavy Haul Association (Heavy Haul 4.0 - Achieving Breakthrough Performance Levels) held in Narvik*, pp 611 - 615, 2019.

2. K. M. Phala, W. Doorsamy, and B. S. Paul, "Detecting and clustering neutral section faults using machine learning techniques for smart railways," *Proceedings of 6 International Conference Machine Learning Techniques for Smart Railways; Proceedings of 6 International Conference of Soft Commuting and Machine Intelligence (ISCMI), held in Johannesburg*, pp 1 - 6, 2019.

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LIST OF SYMBOLS

$\boldsymbol{A}$	Area of the small loops [m²]
$\boldsymbol{N}$	Number of turns [per unit]
l	Length of the windings [m]
π_o	Magnetic constant [4π x $10^{-7}\ V.s/(A.m)$]
π_r	Relative permeability [per unit]
R_l	Resistance [Ω]
R	Radius of the major toroid
Γ	Minor radius
L_l	Inductance [H]
C_l	Capacitance [F]
f	Frequency [Hz]
F_d	Damping force
F_s	Spring force
F_a	Applied force
m	Proof mass
k	Spring constant
w_n	Undamped resonance frequency
Σ	A set of classifiers
ϵ	Distance of the boundary line

C Covariance matrix

$\bar{X}$ Vector that hit the closest point

w Weight vector

v Velocity [m/s]

P Power [W]

θ Angle [degrees]

LIST OF ABBREVIATIONS

RBCT	Richards Bay Coal Terminal
AC	Alternating current
AI	Artificial intelligence
APES	Academic and Professional Editing Services
AWS	Automated wiring system
CSV	Comma-separated values
CT	Current transformer
DBSCAN	Density-based spatial clustering of application with noise
EM	Expectation-maximisation
EMI	Electrical, magnetic interference
GMM	Gaussian mixture model
IoT	Internet of Trains
IR	Infrared thermometer
LTE	Long term evolution
MEMS	Microelectromechanical system
NS	Neutral section
PCA	Principal component analysis
RBF	Radial basis function
RC	Rogowski coil
SVM	Support vector machine
TCP	Transmission control protocol
VT	Voltage transformer
WiMAX	Worldwide Interoperability for microwave access
WSN	Wireless sensor network

CHAPTER 1

INTRODUCTION

1.1 RESEARCH INTRODUCTION AND BACKGROUND

Railway electrification in South Africa emerged in 1923 where most lines were constructed as 3kV DC lines. During 1983 25kV Alternating current (AC) lines were launched, linking the mines to the harbour at Richards Bay. Electrification provided the opportunity to run more trains with more wagons, whilst creating more train slots. The single-phase 25kV AC tapped from the three phases, supplies the electric locomotives. A phase break or neutral section is provided to insulate two phases from the traction substation. This is also conducted to prevent an arc from being drawn across various phases. No existing system monitors or detects failures on the neutral section, apart from the breakers used to detect fault currents on the catenary wire at the traction substation, 30km away.

The neutral section failures are unbalanced and skew arc runners, burnt, loose or slacking balancing droppers and trains, without switching off. The challenge with a fault monitoring system is that with a failure on the neutral section alone, the protection relay neglects to detect the failure unless the catenary wire fails. Fault detection and diagnosis is crucial, mainly in railways, where abnormal events are detected. A detailed root causes analysis is conducted to prevent a similar occurrence. The current method employed to detect immediate and long-term faults is through foot inspections and inspection trolleys, fitted with cameras. This method proves to be inefficient and time-consuming.

Catenary and stay wire were deployed in continuous fault monitoring of the infrastructure to detect wire breaks and pole inclination. The real-time data acquisition was sent to the central command centre [1] and [2]. The intelligent fault monitoring system, utilising wireless sensors is imperative to send and receive data and to detect disastrous events from the vast sensed data to extract meaningful results for accurate fault diagnosis. Fault identification and management can potentially manage risks associated with the neutral section (NS) for accurate prioritisation of resources. A deficiency of such system in the Southern Africa railway fraternity is the capacity of devices (software, cloud storage, processing resources and skills) hindering deploying such advance fault monitoring system. An intelligent NS fault monitoring system on the rail network has the potential to ensure the safety of the overhead network, as a reliable and cost-effective passage of freight trains.

The purpose of this study was to improve the fault monitoring, classifying and grouping the NS faults, based on the impact resulting physical contact between contact-pantograph interaction and environmental conditions (change in temperature), providing an improved accurate fault diagnosis. This is achieved through building a prototype circuit mounted on the NS, housing all the sensors. Afterwards, processing and data analysis methods are employed to assess the intelligent and fault monitoring system for accurate fault diagnosis.

1.2 PROBLEM STATEMENT

Attributable to the high demand of commodity export, additional freight hauling slots are depleted, due to the global demand. Richards Bay Coal Terminal (RBCT) is the chosen site to perform this research. Figure 1.1 displays that the depots are challenged with unreported incidents where NSs are realised to be damaged and failing during pantograph-contact wire interaction. The coal corridor does not have available train slot reserves. Failures directly impact the business. Power-driven methods employed to detect immediate and long-term faults such as foot inspections, and inspection trolleys fitted with cameras are replaced with intelligent, cost effective, remote sensing and diagnostic system that utilises machine learning, wireless sensors and cloud computation. This power-driven method proves to be inefficient, depending mainly on human experience and accuracy [3].

NSs pose a safety risk as the rail network is unavailable for the movement of trains for a specified period were scheduled trains are cancelled, tonnage volumes are lost, including a high cost for equipment replacement. This impacts negatively on business performance and revenue. An established system lacks to detect faults and monitor the condition of the NS. The network relies on the substation breakers to monitor the overloading and fault current on the overhead track equipment, placed 30km apart. It is unable to detect mechanical failures resulting from the loose balancing droppers, arc runners, skew insulation rods and overcurrent/overvoltage when the pantograph slides beneath the insulation [4].

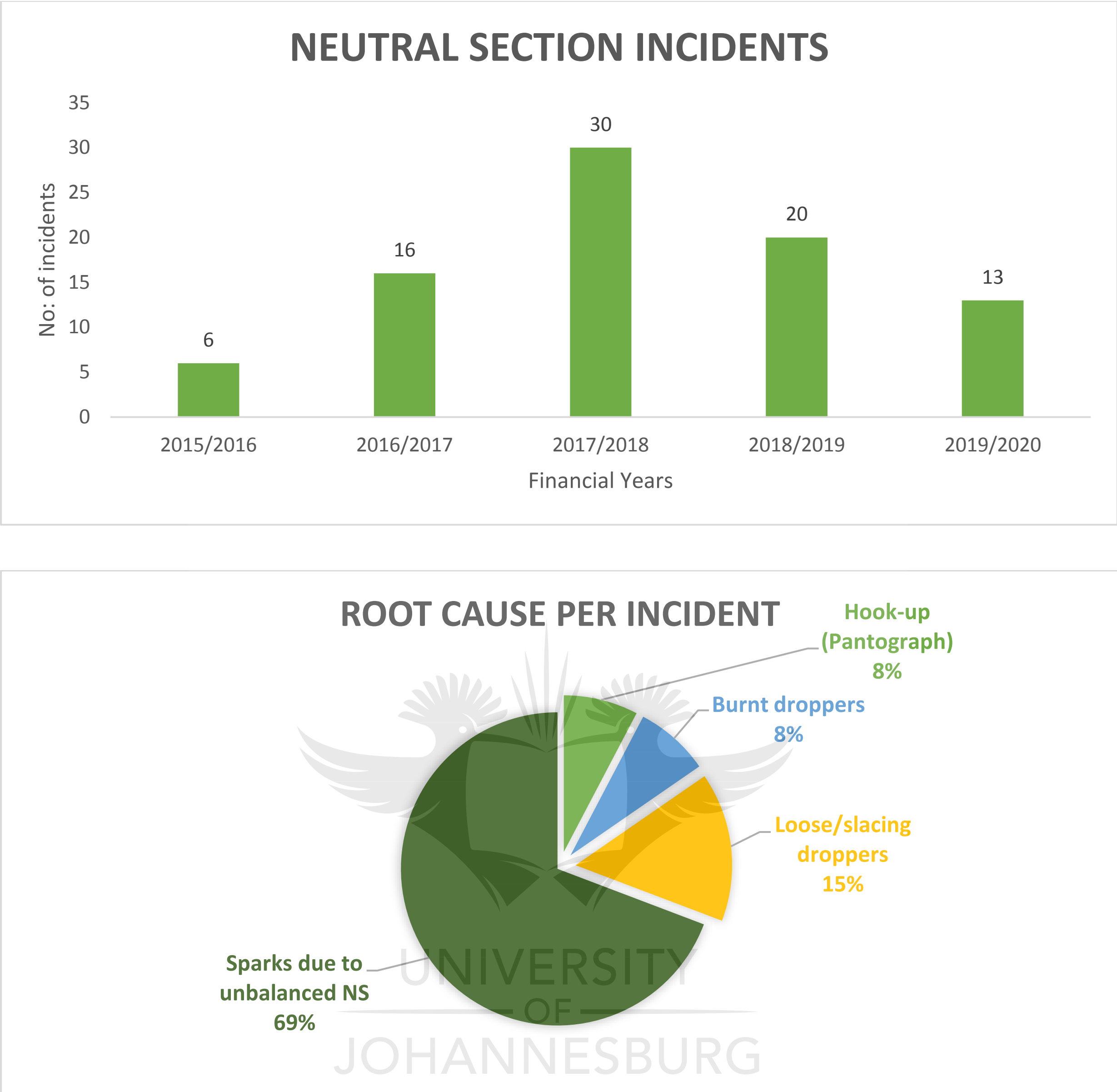


Figure 1.1: Coal corridor neutral section incident statistics and root cause analysis per incident [4]

The intelligent NS condition detection system on the coal line is motivated by the following:

- predicts asset failure and provide proper diagnostic
- increases rail network availability and efficiency
- reduces operation cost, such as corrective maintenance, enabling predictive maintenance
- improves the turnaround time of the training cycle from mines to ports
- increases asset productivity

1.3 AIMS, OBJECTIVES AND DELIMITATIONS

1.3.1 The study aim was to:

- Develop an intelligent fault monitoring system on the coal line using wireless sensor networks to detect failures and classify pantograph events resulting from the NS.

1.3.2 The objectives of the study were to:

- investigate detecting abnormal events, resulting from unbalanced NS, whilst grouping the events consequently
- develop a framework for fault monitoring, classifying locomotives, based on the contact-pantograph vibrations
- investigate differentiating between detected pantograph events from oscillating contact wire events and excessive wind events

1.3.3 Delimitations of the study:

Due to limited time frame and financial resources some limitations are imposed on this work:

- Due to limited time frame only a sample of training data set is collected from onsite experiment as permit proof of concept that machine learning can be applied as a framework of the NS fault monitoring
- There are no transient overvoltage's study of locomotives passing through the NS due to costly instruments to procure such as Rogowski coil and rechargeable battery bank
- Modelling and simulation of protection scheme settings under fault condition at the NS is not executed due to limited substation work occupations and finance cost to accommodate Testing Officer from Technology Management

1.4 STUDY LAYOUT

1.4.1 Preliminary literature review

Chapter 2 outlines the extensive literature review of the NS operation, existing fault monitoring devices in-use, big data, different and applicable machine learning techniques, wireless sensors, their communication technology and lastly work related to the Internet of Things.

1.4.2 Development framework of the fault monitoring system on the neutral section

Chapter 3 delineates the methodology employed to generate, collect, process and analyse the vast amount of sensed data using ThingSpeak™. It also outlines the contribution of the research groundwork of the fault diagnosis, employing the developed algorithms.

1.4.3 Machine learning diagnostic and pattern analysis

Chapter 4 assesses the evaluated machine learning algorithms (K-means and the support vector machine), whilst presenting fault diagnostics of the fault monitoring. The system is completed after the data analysis, evaluation, validation of the K-means and classifying pantograph events detected.

1.4.4 Conclusions

Chapter 5 concludes the study presentation, industry contribution towards the field of railways, whilst proposing future studies.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter presents the literature on an intelligent NS fault monitoring system employing wireless sensor networks to detect the abnormal events, classify the train type and measure the generated temperature. Reported incidents that cited sparking and trains failing to switch, exponentially increased over the past years; this requires an intelligent fault monitoring system, employing a wireless sensor to locate and alert the depot personnel speedier. Infrastructure monitoring and train detection is crucial for productivity and safety, forming fundamental forces of monitoring the overhead infrastructure. Detecting abnormal events is the objective for improving network availability, improving safety during operations, and establishing maintenance activities. Fault identification and controlling enable effective risk management associated with the NS, ensuring accurate resource prioritisation. An extensive study was conducted on NS types and their operation. This chapter focuses on the Arthur Flur NS25 and the types of phase separation employed.

2.2 NEUTRAL SECTION OPERATION

An NS or phase break is an arrangement of wires and insulating devices brought into the overhead track equipment, intended to ensure that two sections are not electrically connected, whilst maintaining a mechanical connection to allow smooth contact and pantograph interaction during the passage of trains [5]. Electrical power is generated in three phases, displaced 120 degrees apart. The traction system uses the single-phase supply. Two phases are used to feed the overhead wires. The loading of the phases should be balanced, ensuring alternating of phases where the overhead wires are supplied. Phase breaks are provided in various sections.

The NS, fitted with track magnets in-between to de-energise the coil, switching the breaker and energising the coil for switching on after traversing through the NS by restoring power to the locomotive [6]. This limits the locomotive from drawing an arc across the various supply phases. The NS is provided to prevent a phase from phasing contact, whilst trains are not switch-off at the assembly.

Three types of NS are specified as dynamic, short, and conventional neutral sections. In South Africa, a short neutral section is employed on the 25kv AC electrification, such as the Arthur Flur NS25, Karl Pfister and Sicat 8WL5545-4D/4F (Siemens type). The Arthur Flur NS25 is the most used on the 25kV AC attributable to the advantage, requiring less maintenance for a more extended period when installed correctly, compared to the remainder of the NS [7].

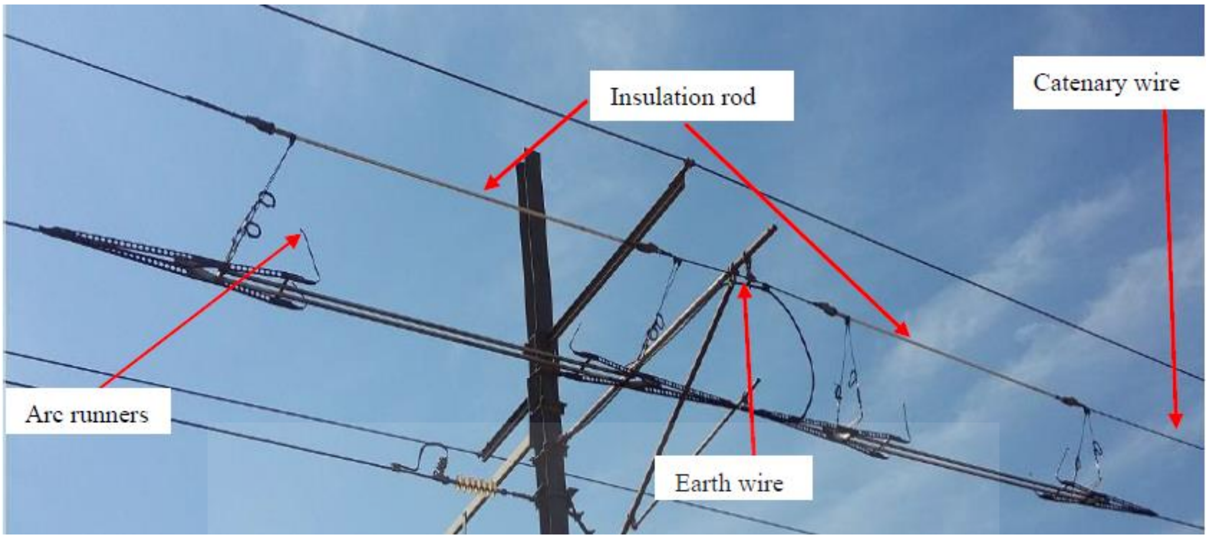


Figure 2.1: Arthur Flur neutral section (NS25) diagram

Three types of phase separations are employed on the single-phase AC rail electrification globally. This is conducted to sustain the load balance from the Eskom supply, the overvoltage or transient caused by the phase split loaded trains switch-off/o traversing the NS' are observed through diverse technologies. The monitoring systems are suitably built for the in-use designs. The speed of the locomotives influences the overvoltage transients, and overcurrent at the NS, hence the track magnets operate the vacuum circuit breaker on/off depending on the train's direction. The nature and slope of the rail track influence the operation of on/off switching of the locomotive. Where track magnets are installed, the radius of the track should be less than 500m, and the slope should not be upwards, facing the direction of the NS.

2.2.1 Three neutral section phase separation types

- **Auto-passing switching method**

The auto-passing switching or automatic changing system method allows the locomotives to automatically switch on/off the vacuum circuit breaker by employing track sensors and onboard vehicle sensors. There are four sensors installed and displaced separately on the track to provide a delay signal for switching the vacuum breaker on/off during the NS. The locomotives are fitted with on-board vehicle sensors, providing commands to open or close the vacuum circuit breaker of the pantograph [8]. Also, the locomotives are supplied with autonomous switching to various phases where the train maintains the notch-on and average speed, whilst traversing through the NS [9]. This method allows the train to pass at the NS without reducing speed and driver intervention. The disadvantage of the auto-passing switching method is that it produces overvoltage, degrading the insulation equipment, concluded as inoperative.

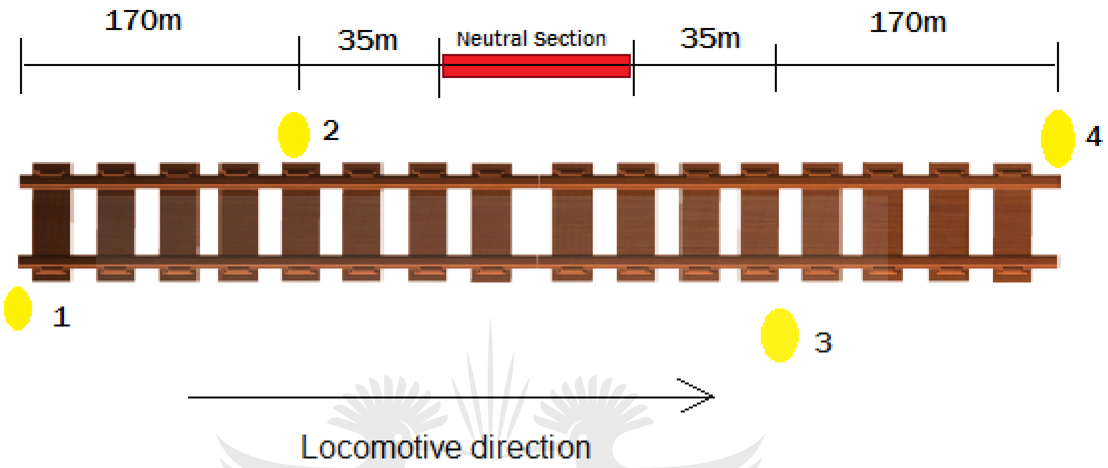


Figure 2.2: Four ground magnetic sensors installed between the tracks

- **On-pole automatic switching method**

This method also comprises ground magnet sensors to switch-off/on the pole-mounted vacuum circuit breaker. The on-pole automatic switching method involves an extensive insulation level system to improve the system whilst preventing the arc from being drawn by the pantograph across the phases of the substation supply [10]. It also does not allow trains to pass the NS' at a different speed; human intervention is critical when traversing through the NS. This method requires scheduled inspections to monitor the condition of the insulation, attributable to seasonal changes and rigorous maintenance.

- **The ground switch automatic method**

The ground switch automatic method is widely employed because it utilises the insulated overlaps, increasing the worth of the locomotive pantograph head with shorter switching times between 0,1~0,15s [11]. At the Transnet Freight Rail Infrastructure, the ground switch automatic method is employed throughout the 25kV and 50kV AC electrification where the dead zone is grounded to the rail, using insulated 97mm² PVC cables. Two ground magnets are fitted between the tracks, placed 45m apart from the NS. The first ground magnet switch-off the on-board vehicle sensor, providing commands to switch-off the locomotive vacuum circuit breaker, including the second ground magnet switch on the on-board vehicle sensor. The process enables closing of the vacuum circuit breaker, allowing the current to be drawn to the motors. This is a costly method attributable to maintenance and replacement of worn-out equipment.

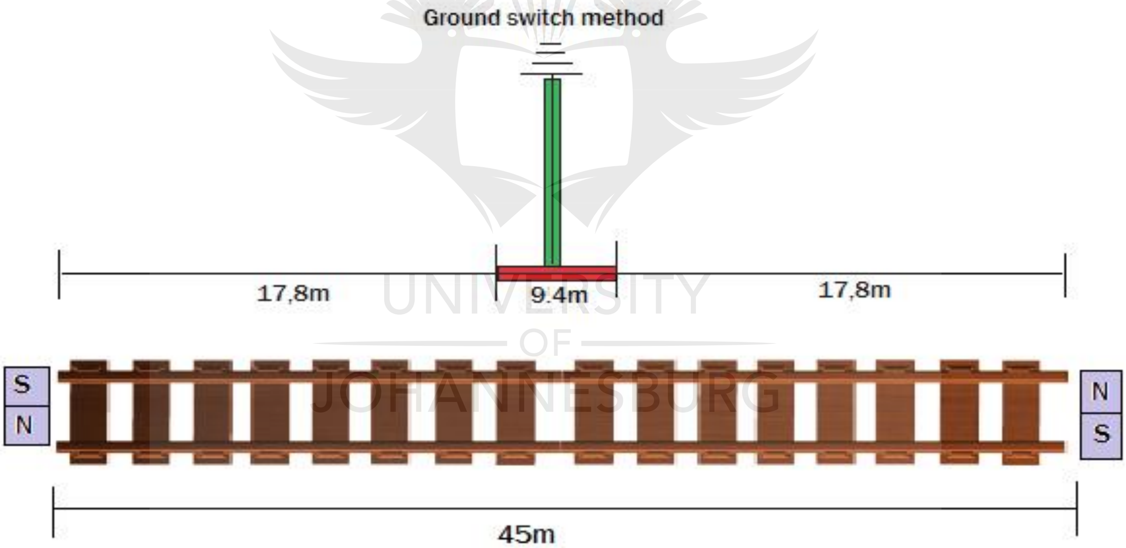


Figure 2.3: The ground switching method

The ground track magnets should be installed correctly. It should be centred, maintaining the required height between the magnets and rail crown. The on-board vehicle sensor polarity is opposite the ground track magnets; the incorrect polarity of the ground track magnets disables the on-board vehicle sensor to command the vacuum circuit breaker to open. The communication process with the sensors requires 90ms, whilst the speed should be less than 120km/h.

2.3 FAULT MONITORING SYSTEMS

An extensive study was conducted including instrument (current and voltage) transformers, capacitive voltage transformers and protective relays [12,] [13], [14], [15], [16] and [17] describe various applications used to detect abnormal events and to isolate the faulty section. These traditional instruments are still in use on the railway network to detect and isolate fault currents and overvoltage's resulting from overhead wires located inside the traction substations. The instrument transformers are coupled to protective relays where the relays are responsible for detecting the unhealthy condition of the network thereby activating the circuit breakers to interrupt and disconnect the faulty section automatically. The relay allows the faults to be detected and disconnected from the network quicker to prevent further damages/interruption of supply to Eskom or municipalities and limiting the amount of damage that could be caused into the national grid.

These instruments are prone to failures due wiring failure, theft and harsh environmental conditions. The transmission of overhead wires is recorded through current and voltage transformers supported over by fibre optic cable. Every breaker is connected to the telecontrol card before it is transmitted to national control for monitoring of the network. Under severe lightning storm these cards are prone to fail affecting breakers to be remotely closed after tripping. Also, capacitive voltage components are prone to ageing when operation over a longer lifespan particularly during harsh conditions. Instrument transformers and relays provide much needed solution in detecting and isolating failure however due to its hard wiring these poses a challenge on transmitting failure even on harsh condition and prone to theft. Wireless detection of failures contributes constructively into safely and reliability of network thus enabling greater availability of network and reduces loss time.

Selected components used in fault monitoring systems are reviewed here as these form critical components of the presented research. The design and operating principles of these components are reviewed, as well as the application of these components into study of fault detection into overhead wires.

2.3.1 The Rogowski coil

In this subsection, a Rogowski coil structure and lumped model of Rogowski coil is reviewed. The Rogowski coil is suitable for low frequencies such fault monitoring of single AC fault on the overhead catenary wire. The Rogowski coil is defined as analogous instrument transformer; however, this device offers advantages, such as light in weight, cheaper, occupies less floor space and flexibility. This device is suitable for fault monitoring system since it linear and can measure even high AC currents [18] and [19]. The Rogowski coil function is to detect failures arising locomotive failing to switch-off where fault currents are recorded. Instrument transformers, such as the current transformer (CT) and voltage transformer (VT), are labour intensive and require ample maintenance ensuring efficient operations.

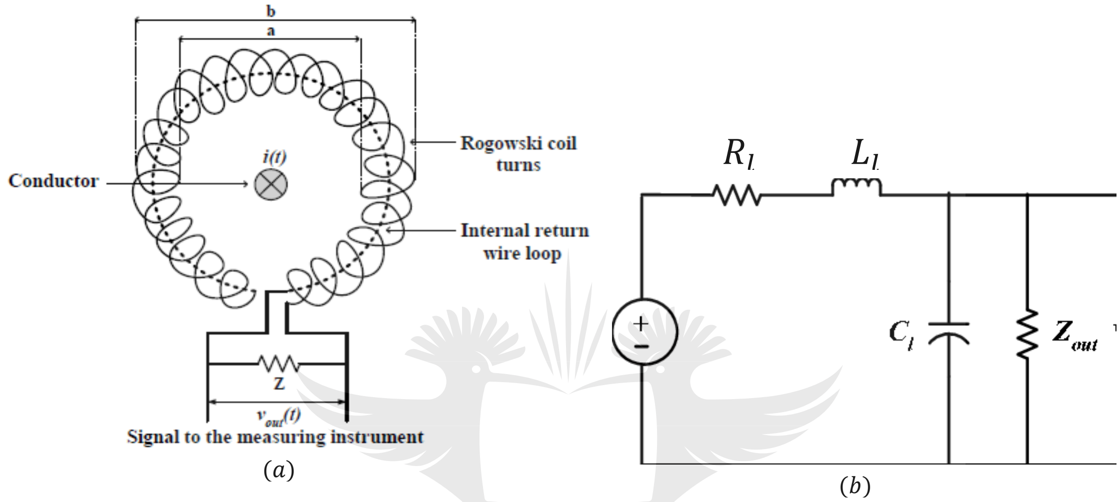


Figure 2.4: (a) Rogowski coil structure and (b) lumped model of Rogowski coil

Rogowski construction

The RC encompasses a hollow toroid coil, tightly wounded in the nonmagnetic skeleton, inducing magnetic field changes, and producing induced electromotive force. The RC is wrapped around the component, or live conductor intended to be measured. The lumped model of Rogowski coil (RC) includes a resistors R_l , capacitor C_l and inductor L_l where p_c is the electrical resistivity, Z_{out} is modelled as the impedance at the terminals, a and b are internal & external radius of the coil. The RC is made of identical turns N on the toroid coil wrapped around and spaced at uniform length l_w. The winding and diameter d of the coil is critical for preserving amenity to the external field. The sensed voltage on the coil is proportional to the rate of change of the current in the straight conductor [20] and [21].

$$R_l = p_c \frac{l_w}{\pi d^2} \tag{1}$$

$$L_l = \frac{\pi_o \pi d}{2\pi} \log \frac{l_w}{\pi d^2} \tag{2}$$

$$C_l = \frac{4\pi^2 \varepsilon_{o(b+a)}}{\log\left(\frac{b+a}{b-a}\right)} \tag{3}$$

The integrated circuit produces the output signal proportional to the current waveform from the output of the RC into the integrated circuit connection. The electrical insulation and safety aspects are vital for the excellent functioning of the RC. The RC should be electrostatically shielded from electromagnetic field coupling. The electrostatic shield reduces the electromagnetic field coupling, whilst increasing stray capacitance for the reduced distance concerning the RC size [22].

During a fault on the line, the circuit breaker attempts to lock-out. The electrical control activates the standby personnel to visually inspect the overhead line to establish the origin and the extent of damage caused. The aim of the system determines the types of the fault cause without visually inspecting the entire section by using the alert messages. The RC detects and measures the fault currents from the trains failing to switch-off, sending alerts to the depot maintenance personnel. RC benefits are listed as follows [23].

Benefits of RC

- it can be enclosed in-between the live conductor without danger
- it is linear and can measure high currents
- no temperature compensation
- the secondary winding may be opened without endangerment
- full current measurement ranging from 5-20000a on a single a coil

Disadvantages of RC

- output of the RC is passed through the integrated circuit to produce the current waveform
- an integrator and a power supply are required

2.3.2 Microelectromechanical systems accelerometer

Figure 2.5: Micro-electromechanical systems accelerometer ADXL345

In this subsection, the micro-electromechanical system (MEMS) accelerometer is reviewed. Accelerometers are designed to measure acceleration in three axis (X, Y & Z), consumes less power and can be used to measure wirelessly integrated with wireless communication circuitry. The MEMS accelerometer was known as a device measuring acceleration (vibrations or motions) and static force (gravity). These devices are widely used, such as on infrastructure monitoring (buildings/bridges), rotation, train tilting, earthquakes and aeroplanes, amongst other things. MEMS acceleration measures in terms 'g' gravitational force, rated 9,82m/s². It is also a vector quantity with direction and magnitude. Recent advance of electronics enabled deploying accelerometers to measure the vibrations, shock, and tilt angles on the railways through wireless communication. These devices are small, consumes low power, cost-effective and easy to install.

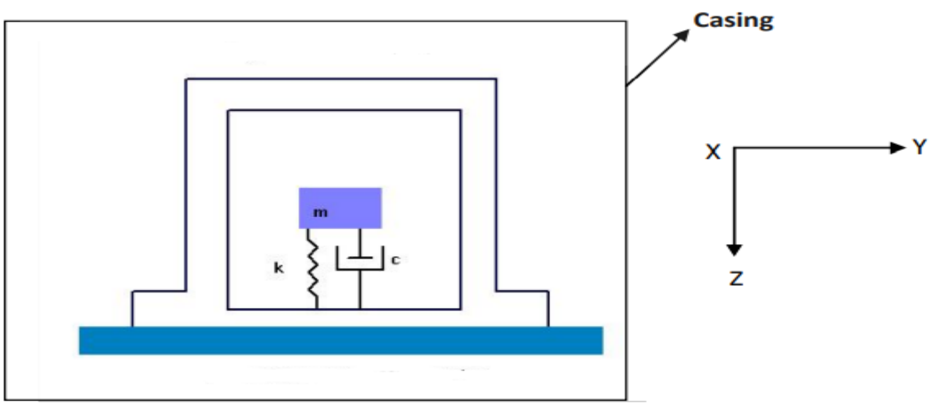


Figure 2.6: Accelerometer schematic diagram

Where?

- m - mass of the body (seismic or proof mass)
- k - spring stiffness
- c - damping coefficient
- a - acceleration

The working principle of the accelerometer

Figure 2.6 illustrates that the mass is attached to the spring stiffness, consecutively attached to a casing. Also, the mass is attached to a damping coefficient parallel to the spring stiffness. Both the spring stiffness and damping coefficient are attached to a casing. The dashboard provides the damping effect from the system. When the accelerometer system experiences a linear acceleration, a force was equalling to the mass of the body times acceleration acts on the mass of the body, causing it to deflect. The deflection is sensed and converted into an electrical signal [24]. The system stabilises through the damping coefficient under the applied acceleration. The three components m, k and c render it sufficient to provide a component that may move relative to sensor frame, and a means to detect the movement.

Deriving component concerning sensor housing

$$F_d + F_s + ma = 0 \tag{4}$$

$$-F_d - F_s = ma \tag{5}$$

$$ma = -cx - kx \tag{6}$$

The sensitivity of the accelerometer is defined by the following

$$a = -\left(\frac{c}{m}\right)\dot{x} - \left(\frac{k}{m}\right)x \tag{7}$$

Many accelerometers with various components exist, intended for their applications. They are constructed with multiple x,y,z-axis holding a high sensitivity to measure even the minute shift in acceleration were the sensitivity ranges from ±2g, ±4g, ±8g or ±16g. The lower gravity force provides more resolution for slower movement; the high gravity force provides more resolution for high-speed tracking. ADXL345 3 axis MEMS accelerometer employs a capacitive sensing principle where the movable body mass is fixed through the mechanical suspension system to a reference frame. The moving and outer plates form the differential capacitance; when force is applied, the body mass deflects. The deflection is measured as capacitance change [25].

ADXL345 features

- free fall detection
- activity/inactivity monitoring
- single/double-tap detection
- tilt sensing application
- small and easy to install
- dynamic acceleration from vibrations and motion
- ultra-low power; 0,3mA standard mode consumption, 40μA in economic consumption mode and 0,1μA in standby mode

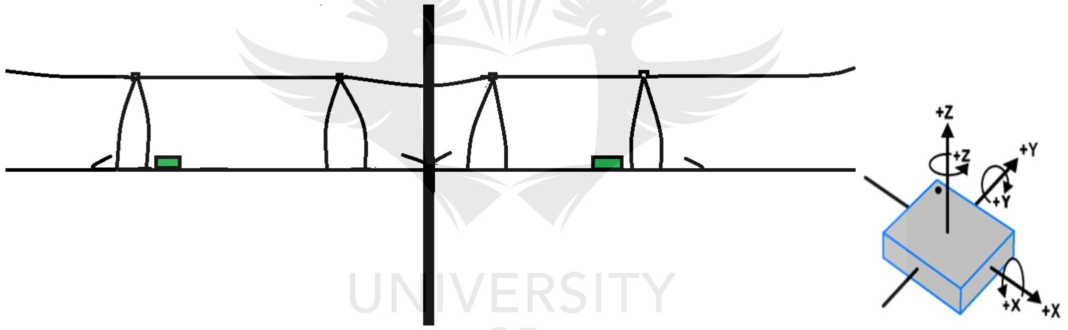


Figure 2.7: Enclosure housing accelerometer installed on the neutral section

The accelerometer is positioned on a horizontal surface; X and Y-axis read 0g regarding the NS. The difficulty arises when the accelerometer is positioned concerning the track. The rail tracks are not positioned flat at a time, particularly on curves. The Z-axis is of insignificant importance since interest is on vibration and tilt angle. The enclosure shall withstand harsh environmental conditions. The intelligent fault monitoring system on the NS assists by locating the exact deviation from the regular operation, supporting the depot to reach quicker from critical events. Any unusual event is detected, processed and conveyed, should the recorded events exist preset values [26].

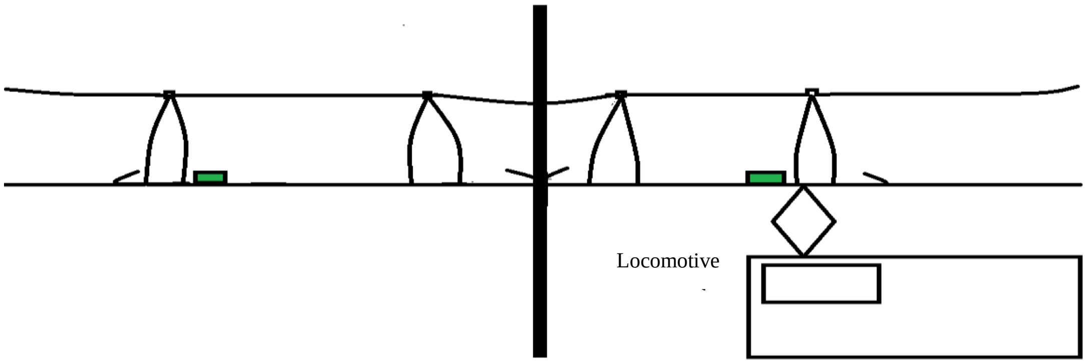


Figure 2.8: Pantograph traversing through the installed sensors

Two enclosure housing accelerometers were installed as indicated in Figure 8, where the first sensor on the right hand detected vibrations, touching the NS and the second sensor on the left hand, as the locomotive pantographs departs the NS. Vibrations through pantograph/contact wire interaction were detected. Unbalanced arc runners were monitored to avoid spark/flash when they pass through it. As soon as the balancing droppers lose position, the accelerometer picks it up and send an alarm to the depot maintenance personnel.

Table 2.1 indicates the cross-axis sensitivity as the percentage of acceleration or gyroscope sensitivity for a provided positioning error. The accuracy of positioning the accelerometer is vital because this does not provide an incorrect reading but influences sending false alarms to the maintenance personnel, responding to a call-out.

Table 2. 1: Comparison between cross-axis sensitivity and orientation error

Orientation errors (θ)	Cross-axis sensitivity ($\sin\theta$)
0°	0%
0,5°	0,8%
1°	1,75%

2.3.3 Non-contact infrared thermometer temperature sensor

Figure 2.9: Infrared thermometer sensor

Temperature measurement often requires direct contact of the object or device with the temperature measuring instruments. However, in the case were high fault currents are produced, non-contact thermometer sensor plays a vital role on measuring the device without being damaged as a result of high fault current being produced due to contactless measuring capability. Various temperature sensors were established with diverse applications. Temperature measurement is often based on the material to be measured. Contact and non-contact temperature types were established. The non-contact infrared thermometer uses infrared light changing in wavelength by rebounding from the measured object. The infrared thermometer (IR) temperature sensor has dual measurement where ambient (Ta) and object (To) temperature can be measured simultaneously from a distance.

The sensor intends to measure the temperature of the NS component under normal and abnormal conditions. The object temperature under abnormal condition differs should the spark/flash generated from the trains failing to switch-off, or when the NS is unbalanced, avoiding the direct contact that must burn the enclosure from the heat generated. The high precision of the measurements depends on the distance from the tested object, angle (field of view) of the surface and the environmental temperature.

2.4 MACHINE LEARNING ALGORITHMS

In this section, the machine learning techniques are reviewed and importance of the algorithms that forms part of the research on fault detection and classification of fault types. The core function of machine learning is to provide intelligent methods, interpreting data and analysis of data to render sound decisions on addressing conditions and fault, detecting infrastructure assets. Wireless sensor network (WSN) developed its reputation as the environment and infrastructure. It is embedded with sensors to monitor the faults, temperature, health and natural disaster for safety by preventing loss of life or damage that may be catastrophic. The infrastructure asset was installed with wireless sensors, predicting when the NS failed, detecting faults resulting from trains failing to switch off. Three types of machine learning techniques are identified, such as supervised, unsupervised machine learning and reinforced learning [27].

Machine learning is beneficial

- improved monitoring of environmental conditions, such as soil erosion sensors, to alert and render an informed choice for human beings to be aware of the damaged of the soil [28].
- industrial monitoring for increased automation to improve predictive maintenance and trolley inspections on the railway lines [29].
- health and medical monitoring to improve the medical research for improved cure.
- surveillance monitoring to improve security and cyber threats [30].
- wildfire monitoring to vacate the endangered species safely [31].
- providing scientific viability to construct an accurate model for a complex environment.

These are some of the main categories that machine learning algorithms are broadly categorised into the following three algorithms.

- Supervised learning requires training of data. This type of learning is not immediately suitable in the context of the presented research because training data needs to be available. The data needs to be split into training and testing were labels of the data is performed with expected output. This learning consumes a lot of time were data is trained and labelled [32].
- Unsupervised learning does not require training examples for building of a machine learning model, thus these are immediately available to be used in the presented system for

fault pattern analysis/detection. This learning makes it suitable for the fault detection/pattern recognition.

- Reinforced machine learning: In this type of learning, the system studies a rule of how to act, reflected the process without knowing whether it reached the goal [33].

2.4.1 Supervised machine learning

Supervised machine learning requires training of data, as the label reveals, refers to a method where the system is supervised. In this kind of learning the machine is provided with a set of inputs with the expected outputs for each example. This type of algorithm is commonly used on fault detection and tracing, using the WSN. The fault is usually classified based on features, such as voltage, and the current frequency. This algorithm was further explored for possible options to address the intelligent fault monitoring system on NS, particularly predicting how and when the NS fails because it was unbalanced.

Certain employed algorithms are:

- support vector machine (SVM)
- neural network
- k-nearest neighbour (k-NN)
- decision tree
- Bayesian statistics
- linear regression

The support vector machine

SVM forms part of the research were recorded events of the contact-pantograph interaction are classified. The events or non-event labelled are classified using SVM kernel function The SVM is a supervised learning model, based on a classifier model, classifying between two categories by creating a hyperplane in the high dimensional input space, used for classification. Various SVM kernel functions are identified, such as linear, non-linear, polynomial, Gaussian kernel, and a radial basis function (RBF). SVM kernel performs well, providing continuous data, and that algorithm can learn more from fewer samples. SVM performs well on classifying detected faults, provided that input data are trained correctly with no errors. The set input data (features x) are required to train the algorithm [34].

$$x = [x_1, x_2, x_3, \ldots\ldots x_n] \tag{8}$$

The label denotes the class

$$c_i = \in \{c_1, c_2, \ldots\ldots c_j\} \tag{9}$$

This belongs to

$$l_i = \int {}_{0\ if\ x \in c_{j;j \neq i}}^{1\ if\ x \in l_{i;}} \tag{10}$$

The training set X is defined as a set of N’s, containing values such as:

$$X = \{x^t, l^t\}_{t=1}^{N} \tag{11}$$

The main objective for this algorithm is to learn data and their labels generated from the detected fault to train and classify the new output. The SVM classified the output data from the locomotive pantograph vibrations to detect and classify the train type. Each track has a dedicated train type, running from the mines to the coal terminal harbour [35].

2.4.2 Unsupervised machine learning

Unsupervised machine learning requires no labelling of data which leaves it to the algorithm to find pattern/fault analysis. Unsupervised machine learning refers to a process where the system is not monitored whilst functioning automatically which makes is it suitable for this research. The data is readily available to use for finding patterns or groups. The system adopts the best solutions based on the input. The algorithm is conducted unsupervised. The clustering method is performed based on the collected data. The similar sets are recognised and classified for various patterns on the data collection.

Specific employed algorithms are:

- principal component analysis
- K-means clustering
- k-medians clustering
- density-based spatial clustering of application with noise (DBSCAN)
- mean-shifting clustering

- Gaussian mixture model (GMM)
- Agglomerative hierarchical clustering

The principal component analysis

The principal component analysis (PCA) is a popular unsupervised machine learning technique that derives low dimensional features from a large set of data. On this type of the algorithm, there is no teacher present; this is mostly used on the data compression field. It extracts the vital information concerning principal components, whilst grouping the pattern accordingly. The PCA also visualises high dimensional data where required features are extracted, and the unused data disregarded. It detects patterns from the provided inputs and group them, conducting descriptive modelling without the help of a person [36].

The analysis commences by deriving the first principal components random vector of features:

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix} \tag{12}$$

With a population variance-covariance matrix

$$Var_{(x)} = \Sigma = \begin{bmatrix} \sigma_{\frac{2}{1}} & \sigma_{12} & \dots \sigma_{1p} \\ \sigma_{21} & \sigma_{\frac{2}{2}} & \dots \sigma_{2p} \\ \sigma_{p1} & \sigma_{p2} & \dots \sigma_{\frac{2}{p}} \end{bmatrix} \tag{13}$$

After the summation of population variance-covariance matrix, the set of features are represented as follows $x_{1,\dots}x_p$ is a normalised linear combination of features.

$$z_1 = \varphi_1 x_1 + \varphi_2 x_2 + \cdots + \varphi_p x_p \tag{14}$$

PCA algorithm

- write the datapoints into row vectors, such as $x_1, x_2, \dots x_p$
- normalise the data by inserting them into a matrix, centre the data subtracting off the mean of each column
- calculate the eigenvalues and eigenvectors

- arrange the columns into an order of decreasing eigenvalues
- plot the data PC1 against PC2

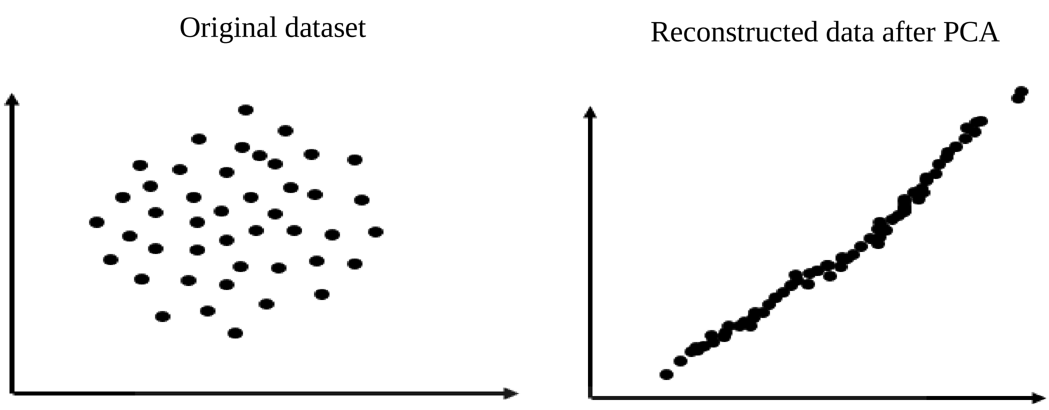


Figure 2.10: Computing the set of vectors and their dimensionality reduction using the principal component analysis

K-means clustering

Readily available of data makes K-means suitable to group the dataset based on their similarity. The clustering algorithms involve several types; not all provide models for their clustering to be grouped based on the similarities. K-means algorithm meets the criteria because it is quicker, easy to implement and capable to handle big data. K-means clustering algorithm is a way of grouping data in the cluster, based on their similarity. The algorithm searches for hidden patterns, whilst objectively classifying the measured raw data from sensors. There are no target variables from this algorithm; it usually self-trained identifying areas lacking the expected outputs or results [37] and [38].

- K-means algorithm
- starting point

Put k randomly where the measured data to be clustered $y_1{}^{(0)}; y_2{}^{(0)}; \ldots \ldots y_k{}^{(0)}$

Allocate each measured data to the group which has the closest centroid

$$x \in l_i{}^{(k)}\ if\ d(x, z_i{}^{(k)}) < d(xz_i{}^{(k)})$$

$$i = 1,2, \ldots, k; i \neq j \tag{15}$$

- Learning
    - Clustering algorithm
    - Calculate the distance to each cluster k centroid

$$d(x_j, y_j) = \sqrt{(x_j - y_j)} \tag{16}$$

Recalculate all the data points of the cluster

- Application
    - Repeat the process until the data points do not converge anymore

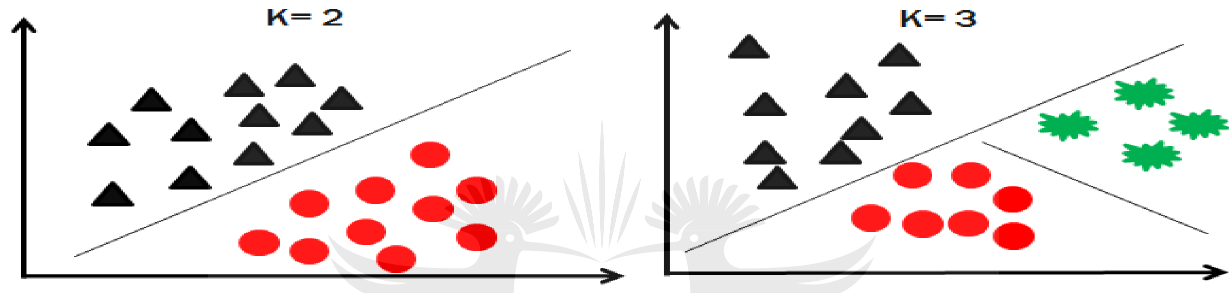


Figure 2.11: Grouped data, based on their similarity

The silhouette plot

The silhouette evaluates the cluster numbers. The silhouette plot indicates the degree of distance of each point in one cluster [39]. The silhouette plot is implemented after applying the K-means, determining separation degrees between the clusters.

The silhouette plot of one data can be defined as follows:

I = data sets in the cluster, i=1,2, 3, …

a = average distance of i to the points in the same cluster

b = minimum average distance of i to points in another cluster

$$s_{(i)} = \frac{b_{(i)} - a_{(i)}}{max\{a_i, b_{(i)}\}} \ if \ |c_i| > 1 \tag{17}$$

$$s_{(i)} = 0, if \ |c_i| > 1$$

$$s_{(i)} = 1 - \frac{a_{(i)}}{b_{(i)}}\ if\ a_{(i)<} b_{(i)} \tag{18}$$

$$s_{(i)} = 0\ if\ a_{(i)=} b_{(i)}$$

$$s_{(i)} = -1 - \frac{a_{(i)}}{b_{(i)}}\ if\ a_{(i)>} b_{(i)} \tag{19}$$

Silhouette coefficients

$11 \leq S_{(i)} \geq -1$

+1: indicating points distanced from neighbouring cluster

0: indicating points not distinctly in one cluster or another cluster

-1: indicating points assigned to the incorrect cluster

K-medians

During instances where the K-means fails attributable to its disadvantages, K-median is another clustering algorithm similar to K-means, except that it does not group centre points using mean; instead, it uses medians. K-median is less sensitive to noise and outliers attributable to its robust. It is not easy influenced by the extreme mean values [40].

Density-based spatial clustering of application with noise

Condition monitoring and fault detection result in high dense data where the algorithm needs to detect any anomalies whilst clustering the data into valid or invalid abnormal events [41]. DBSCAN is an unsupervised machine learning algorithm, clustering the data into groups such as K-means. DBSCAN requires two parameters radius (Eps), representing the radius of the neighbourhood around point P; the number of minimum points in the neighbourhood with MinPts forms the centre. This algorithm does not require a preset number of clusters comparable to K-means. It also identifies outliers as noise, unlike mean-shifting, including them as clustering even if the data point is incorrect.

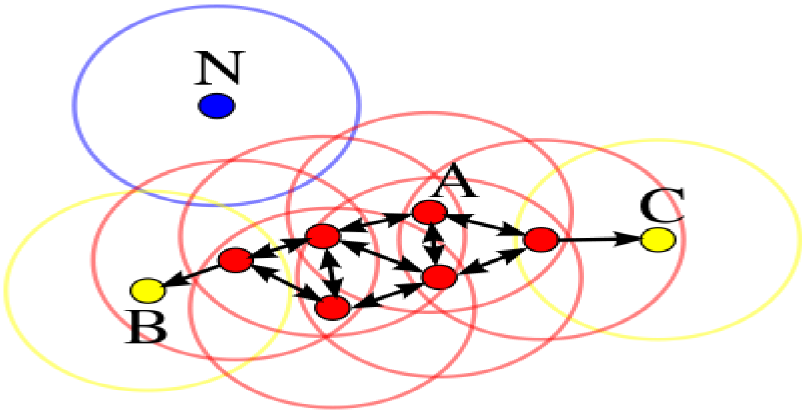


Figure 2.12: Density-based spatial clustering of application with noise: Density-based discovering clusters

Figure 2.12 comprises four minimum points (A, B, C and N). The core points are emphasised in red. Border points B and C do not present the core points. The points form part of the cluster through A and the core since they are rechargeable from core points. Core points and point A are rechargeable from each other, thus forming a single cluster. The blue point (N) is considered as an outlier or noise since it is not rechargeable from other points and does not form part of the core points [42] and [43].

DBSCAN algorithm

- DBSCAN splits the data set into dimensions
- DBSCAN initiates a random point of counting points belonging to the identical profile
- if the data set is not assigned into a cluster, a new cluster is created, and all the density points are grouped as a core point
- after iteration from the visited and non-visited points, the non-core points are grouped into a nearby group of clusters. If not grouped into nearby clusters, it is regarded as noise or an outlier

(a) Before applying DBSCAN algorithm (b) After applying DBSCAN algorithm

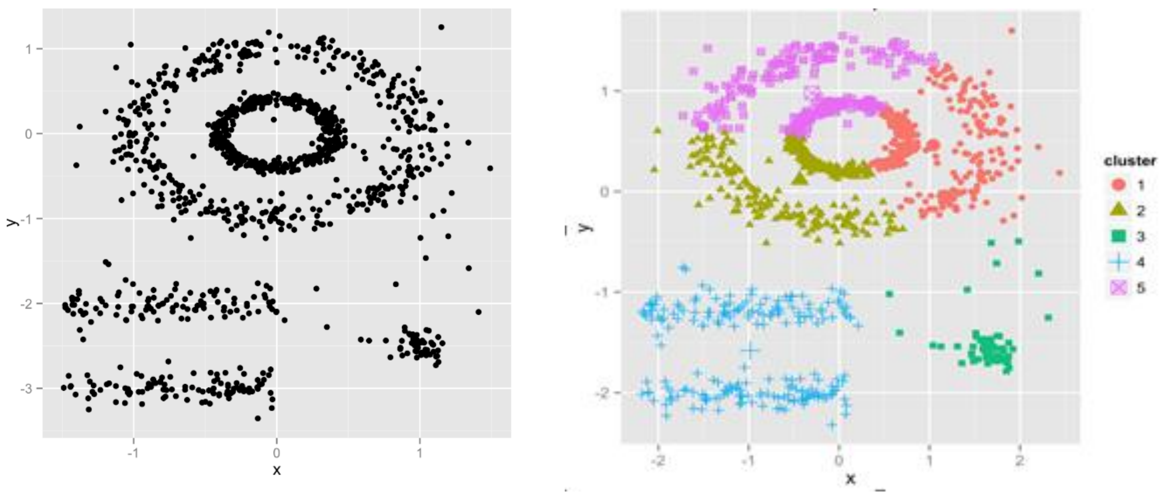


Figure 2.13: High density-based clustering, discovering five clusters in large data set, generated through a Matlab® analysis

Mean-shifting clustering

Mean-shift is an unsupervised machine learning algorithm employed to detect the moving object. The NS device is tracked as the target object to check if it is balanced or unbalanced. Mean-shifting is centroid-based similar to K-means; it utilises a non-parametric kernel function to establish a similar object to its original resemblance [44]. In a case where classifying train types based on vibrations and detecting fault currents, the algorithm falls short. Its application is more used on image processing and video tracking of a moving object. The accuracy of the mean-shift cluster relies on the proper selection of the kernel bandwidth. The kernel bandwidth influences the outcome results from the vibrations generated from the pantograph-contact wire interaction.

The Gaussian mixture model

The GMM is a flexible and probabilistic algorithm employed to cluster the data set. GMM may be used to perform soft (fuzzy) or hard clustering, where the number of clusters needs to be selected before resuming the modelling [45]. The GMM is mostly applied on density estimation, model weather observations, and image segmentation.

GMM is provided by the following formulae:

Where M ε N are mixture models

πj ε [0,1] are mixture weights

Pj ε x are mixture covariance

$$N(x, \bar{x}, P) = \frac{1}{(2\pi)^{n/2}|P|^{1/2}} e^{-1/2(x-\bar{x})^{T} p^{-1} (x-\bar{x})} \tag{20}$$

The expectation-maximisation algorithm

The expectation-maximisation (EM) algorithm is a mathematical device used to model the data in the presence of latent variables. fault monitoring system are occasionally bound to transmit missing values (latent variables), attributable to sensor node error or hardware malfunction. Where missing values are indicated, though continued modelling of the existing data is required, EM is applied to establish the optimum variable parameters. EM comprises two steps, indicating the expectation (E)-step and the maximum (M)-step, derived from the EM algorithm [46].

Expectation-step

The E-step is the first step in the existing data set. This step is employed to estimate the value of the missing variables. Expectation value is high when the points are assigned to the correct or reciprocally. The following formula is used;

$$E - step\ Q_{i,y}{}^{(t+1)} = P_{\emptyset\,(t)}[Y = y|X = x_i] \tag{21}$$

Maximisation-step

Once the missing variables are estimated from the E-step, the parameters are updated. New probability values are calculated for each variable and updated iteratively. The following is used:

$$M - step\ \theta^{(t+1)} = argmaxF(\theta^{(t+1)}, \theta) \tag{22}$$

Hierarchical clustering

Hierarchical clustering is the unsupervised machine learning algorithm attempting to cluster the data set in hierarchy groups. It is divided into the agglomerative method and divisive method clustering. Agglomerative hierarchical cluster iterates bottoms up where each data point forms a cluster and merge with other clusters until a single cluster is formed. An agglomerative hierarchical cluster is visualised using dendrogram. A Divisive hierarchical cluster is an opposite of agglomerative cluster. The data set is grouped as one cluster, iteratively separating the clusters until one cluster object is formed [47].

2.4.3 Reinforcement learning

Reinforcement machine learning refers to a process where the algorithm relies on experience to perform its function. The reinforced typically learn from the environment and feedback signal is provided to complete the tasks as part of rewards for the work executed. For the sake of this report, reinforced is not reviewed on viable options to address the scope and research question [48].

Certain algorithms employed are:

- q-learning
- deep q-network
- deep deterministic policy gradient
- state action reward state action (SARSA)

2.5 WIRELESS SENSOR NETWORK TOPOLOGIES

Wireless sensor networks (WSN) topologies and communications technologies are reviewed on this subsection as the WSN is proving to emerging technology in the field of infrastructure monitoring thus operating autonomously [49]. WSN is used in a specified area to collect and send information for processing and analysis. Various topology types are employed, depending on the system requirements and desired output. These topologies are efficient and dependable for fault detection and condition monitoring processes as they can withstand severe environmental condition [50]. The WSN is a combination of sensors, spatially dispersed to measure or monitor physical or environmental conditions. WSNs offers more advantages than the traditional hard-wiring method [51].

Wireless sensor network application

- military
- industries 4.0
- hospitals monitoring patients
- disaster monitoring
- intelligent transportation service
- smart building or home appliances
- agriculture

Factors to consider

- production cost
- type and make of sensors
- robustness of the sensors
- position of the sensors for accurate measurements
- communication range and bandwidth
- energy supply
- data aggregation
- network topology
- quality of service (QoS)

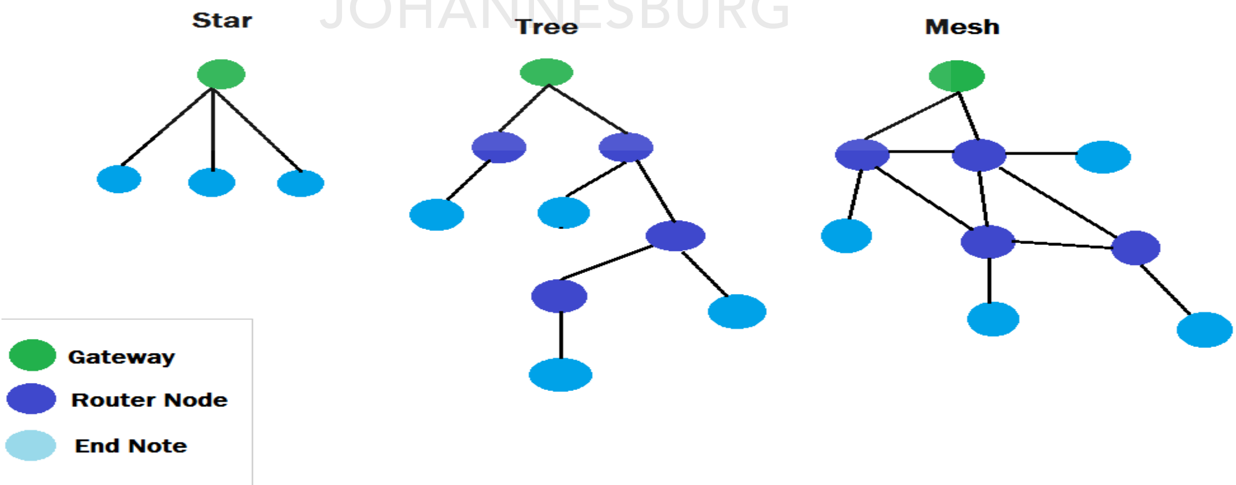


Figure 2.14: Wireless communication technologies

Star

In star topology communication, each end node connects directly to the gateway where a single gateway may send and receive data. On this type of system, the end node is not permitted to direct a message to one another. The benefit of this type is that less power is used and the gateway must be nearer to the conduction range of the individual end nodes. Shortfalls are identified; should the gateway be faulty, the end node would not be able to transmit data.

Tree topology

On this type of topology, the end node is connected to the router node were all the nodes feed into a gateway. The end and router nodes check for communication signal between them before transmitting to the gateway. The shortfall identified in this process is that it relies on the bus cable. During failure, all the communication routes terminate. Tree topology is widely used on fault detection systems because it uses less energy, with superior completion r in systems with less neighbour nodes.

Mash

Mesh topology enables data to be sent between nodes within the range. This is one of the complex systems enabling vigorous communication and a flexible network. The disadvantage of this topology is that it needs to emphasise on all the devices before communication may be conveyed. It consumes enough energy quicker compared to other topologies.

2.5.1 Wireless sensor network communication technologies (hardware)

The short-range distance between the sensor and gateway can be established through Bluetooth, ZigBee, or Wi-Fi. In this case, a hypothesis comparison, ZigBee IEEE 802.15.4 outweighs other devices because of its lower power consumption, lower cost and easy to integrate with other micro controlling devices [52], [53], [54], [55] and [56]. The ZigBee based WSN collect and send data from sensors (accelerometer, temperature, current and voltage) through the router as an access point. The sensors are connected to the Arduino pro mini where the measured data are transmitted to the cloud (ThingSpeak™) through the ESP8266 Wi-Fi module for private storage and the simulation purpose analysis [57].

ThingSpeak™ applications:

- collect data from the sensor installed
- analyse and visualise data online and offline
- react to the abnormal event by sending alarms in real-time

Table 2.2 represents five wireless technologies used for comparison; the worldwide interoperability for microwave access (WiMAX) is also included amongst the four most used short-range wireless devices with low power consumptions. GSM/GPRS is included for long-range applications and sending alerts to mobile devices.

Table 2. 2: Comparison of wireless sensor network technologies

	WiMAX IEEE 802.16	**Wi-Fi IEEE 802.11 b/g/n**	**ZigBee IEEE 802.15.4**	**Bluetooth IEEE 802.15.1**	**Ultra-wide band (UWB) IEEE 802.15.4**	**GSM/GPRS sim900**
Data rate	10-40Mbits/s	11-80Mbits/s	20-250 Kbit/s	1Mbits/s	100Mbit s/s	32/48kbits/s
Range	40km	100m	10-100m	10m	10m	30-35km
Network topology	Point to hub	Point to hub	Ad hoc, peer to peer, star or mesh	Ad hoc, small networks	Ad hoc, peer to peer, star or mesh	Point to hub
Frequency	2-11 GHz	2.5GHz	2.4GHz	2.4GHz	3-10.6GHz	850/900/1800/1900 MHz
Power Consumption	Very high	High	Very low	Low	Low	Very high
Typical applications	Mobile broadband connectivity, digital subscriber line, smart grid and metering	Wireless local area network connectivity, broadband connectivity	Sensor network, industrial controls and monitoring,	Telephones, printers, laptops, headsets, cameras	Short distance radar, automotive, aviation and retail inventory	Mobile broadband connectivity, digital subscriber line, telephones, printers, industrial controls and monitoring, smart grid and metering

2.5.2 Wireless sensor network protocol stack

WSN protocol comprises five layers, indicating the application layer, transport layer, network layer, data link layer and the physical layer. These layers purposely aim to address challenges, such as conserving energy, fault tolerance, network security, data aggregation, whilst providing accurate sensor functioning. The application layer is the first, comprising various software applications for sensing. The transport layer is responsible for reliable data delivery from the application layer, using a transmission control protocol (TCP). The network layer is responsible for transmitting the measured data to the sink.

The data link layer provides multiple access of neighbour nodes with sink nodes to avoid collision. The layer must be highly efficient to avoid congestion, such as buffer overflow and packet collision. Lastly, the physical layer responsible for converting the bit data from datalink into a signal and should be usable for the end-user.

2.6 WORK RELATED TO BIG DATA, FAST DATA AND SMART DATA

2.6.1 Big data

The importance of big data is due to increased scheduled inspections and new infrastructure monitoring sensors were huge amount of data is generated that requires a software tool to store, process and analyse at a faster rate. Big data is defined as data, large enough in volumes to be handled by an ordinary software device that can store, process, analyse and the rate the data transmitted as higher velocity [58]. The big data come from wireless sensors, rail and signalling equipment and machine vision cameras with a higher resolution. Line inspections and fault monitoring defects are captured, requiring big data to be used to evaluate and analyse the data quicker. The rate of producing data over long-distance requires a big data approach. The immediate increase in research and technology development on the Internet of Things (ICT), WSN (mobile devices, sensors) and cloud computing (web-based application) enabled the massive amount of data to be decentralised through big data. Big data is well explained when the three V model (volume, velocity and variety) converses with the extensive infrastructure network. The data acquisition, storage, processing, and analytics of the network are processed faster and smarter [59].

Volume

Volume refers to the dataset volume derived from accelerometers, temperature sensors, lasers, gyroscope, RC, machine vision cameras and enormous and unstructured crack pressure sensors. The continuous fault monitoring systems over long distances repeatedly increase the data size, rendering it difficult for the traditional software devices to process and analyse the data. Currently, 4petabyte of data is created on Facebook, 4terabyte of connected cars and 28 petabytes of wearing exercising devices are created daily. The data volume is expected to surge over 44zetapyte by the end of 2020 [60] and [61]. These large unstructured data volumes require machine learning algorithms to be processed and analysed.

Velocity

The speed at which sensor-enabled accelerometers, temperatures sensors, gyroscope and current measurement must be in real-time. All additional data from the enabled sensors are transmitted into ThingSpeak™ for storage and analysis. Faster Internet access allows the sensors to send alerts in real-time, whilst enabling cloud computing to process and analyse the data faster.

Variety

The diversity of data from various input devices, such as accelerometers, temperatures sensors, gyroscope, and current measurement, are used in a fault monitoring system. The received data are stored, processed and analysed, using machine learning algorithms, such as K-means and faulty bins, grouped to be diagnosed.

The two more Vs emerged over the past years, indicating veracity and value from IBM [62]. Veracity refers to genuine data produced from fault monitoring sensors, identifying devices employed to process and analyse the data. ThingSpeak™ and K-means were employed in this research to extract and reveal meaningful results. The data value is also vital as it enables meaningful findings.

2.6.2 Fast data

As the recorded data is transmitted through the cloud, real-time processing and analysis is essential for anomaly detection to prevent damages and further interruption to the rail network. Fast data allows the contact-pantograph interaction to be transmitted and detected in real-time. Fast data, also known as computing stream in real-time represents data in motion; fast data could analyse, process, and decide in real-time in milliseconds. Fast data observed the trend of ever-increasing data stream computing, whilst enabling minimal latency with complex analytical devices to identify deviation of defects faster. The data processing speed and analysis required a stream computing approach. Big data cannot act on live streams of enormous data files for informed real-time decisions [63]. Fast data use artificial intelligence algorithms for informed decisions. Mostly the algorithms learn from the data without the training set of data. Currently, an autonomous car uses stream processing [64].

- **Fast data must include the following characteristics**
  - Make smart and real-time verdict: the system should act upon non-conformances in real-time in a case where the NS failed and diagnose the failure. Identical to an autonomous car fitted with sensors, the stream computing should enact immediately on the detection, preventing human fatality carnage.
  - Data aggregation/filtering: The system should filter unwanted data from the generated data, whether structured or unstructured. The system should not detect failures but provide solutions, such as identifying when to perform predictive maintenance or when to send alerts to the driver during unfavourable weather conditions.
  - Spot trends, correlations, and patterns: The algorithm should establish hidden patterns or similar features, thereby grouping the similar feature. The system should eliminate outlier or noise whilst only conveying the results.
  - Perform complex analytical representations: The algorithms should be analysed with minimum intervention, and act speeder on the data where informed decisions are executed in real-time; big data are stationary and time-dependent, lacking the much-needed complex analysis to enact on the live streams.

2.6.3 Smart data

The recorded events from the onsite experiment must depicts meaningful achievement were the data is feasible to be transmitted to maintenance personnel in a case of emergency. Smart data is data that is filtered, structured, cleansed digital information, collected from smart sensors transmitted to the dashboard for data analyses and consolidation [65]. Smart data is often associated with artificial intelligence (big data and machine learning.) In the Internet of Things, smart enabling sensors monitor the physical and environmental, used with artificial intelligence (AI) algorithms. The term “smart” means data entrance, intelligent to decide without sending the data to the cloud or central processing software [66]. The fault monitoring system must immediately identify deviations between contact-pantograph interaction and classification of train types. The data should be filtered and structure-based, online type, locomotive class, and fault type.

2.7 THE INTERNET OF TRAINS

The Internet of Trains (IoT) is an assembly with devices embedded with sensors and connectivity, including an exchange of information from the object and user. Billions of devices and its application are connected into the Internet, including mobile devices and computers, the trend is predicted to increase exponential over the next decade. IoT is a network platform were infrastructure assets can be accessed through the Internet [67]**.** Condition monitoring, pantograph fault detection, and contact wire provide an accurate assessment and precise fault diagnosis [68].

Several IoT platforms were developed recently, such as Oracle, Microsoft Azure, IBM Watson and Amazon automated wiring system (AWS), connecting sensors to the cloud for storage and cloud computing. These platforms support software facilitating the entire process, from data collection to communication with cloud computing, using a web-based app [69]. This part of the work describes the process behind acquiring and storage of data, using the ThingSpeak™ platform. The process comprises five layers, indicating data acquisition, interconnection, integration, analytics, and the cloud [70]. The acquisition layer comprises sensors, such as accelerometer ADXL345 and a non-contact infrared temperature sensor. Each sensor conducts the measurements and send them to the ensuing layer where it is processed.

The interconnection layer formed the gateway path for all the measured data to be transmitted to the ensuing layer, employing a GPRS/GSM module suitable for a more extended range. Long term evolution (LTE) is one of the most preferred communication systems for machine to machine devices and IoT. After determining the suitable method of wireless communication, the most suitable network topology was selected for the data gateway through integration. An analytic layer, such as K-means clustering was applied subsequently, grouping the data based on their similarities. This action insisted on rendering an informed decision about the asset condition before assuming the train operation, thus causing an accident. Lastly, this layer could perform data aggregation, applying machine learning techniques. The system, upon receiving data from sensors, processed, and filtered unwanted data, generated from the IoT sensors. Once the raw data became meaningful, anomaly detection and clustering analytics were applied.

2.8 CONCLUSION

This chapter presented the types and operation of NS used on the 25 & 50kV AC used to separate the different phases from traction substation, fault monitoring devices in use, wireless sensor networks, big data, Internet of Things and also machine learning techniques were reviewed inline to grouping and classifying dataset for the purpose of this research. Modern fault monitoring and pattern analysis have advanced due to the progression of computational intelligence resulting into a demand for railway infrastructure embedded with smart sensor to increase the safety and reliability of the real-time instrument inspections and fault monitoring.

CHAPTER 3

DEVELOPMENTAL FRAMEWORK OF THE NEUTRAL SECTION'S FAULT MONITORING SYSTEM

3.1 INTRODUCTION

As opposed to increasing the frequency of scheduled inspections and time-based maintenance activities to alleviate unreported failures, an intelligent fault monitoring system is proposed, detecting impending failures, classifying the faulty locomotives based on the number of pantographs. Continuous infrastructure monitoring embedded with wireless sensors connected to the cloud proved to emerge particularly in investigating the uncertainty of infrastructure failures. Efficient methods are developed to address this uncertainty. This section focuses on exploring how the fault monitoring system contributed to the existing methods used on the overhead catenary wire since no definitive devices are present to detect failures before and after the failure by applying diagnostic algorithms.

This chapter aims to investigate the methods that could be employed to address the aforementioned unreported shortfalls arising from the impending failures. The NS has two insulation rods, typically used to separate the attached phases into arc runners. Part of the contribution towards the field of fault monitoring would also detect the condition of the insulation rods, determining whether they are balanced. Thermal detection of the NS return wire object from both ends also formed part of the analysis. Lastly, data analysis and applying the system classified the locomotives, were based on the pantographs.

3.2 ANALYSIS AND APPLICATION OF THE FAULT MONITORING SYSTEM ON THE NEUTRAL SECTION

3.2.1 Data acquisition and processing hardware

Pantograph and catenary wire are essential components of the current collection system for locomotives in the rail network. The contact wire, rendered pantograph suspended by catenary wire through droppers, whilst the pantograph was mounted on top of the roof through a frame fitted with a spring by exerting a force to lift the pantograph head [71]. Data acquisition for the NS fault monitoring system is achieved through placing the built prototype installed on the Arthur Flur overhead wires, as indicated in Figure 3.1. The enclosures housing the sensors were placed on both side of the NS between the arc runner and insulation, detecting incoming and outgoing pantograph interaction. This is conducted to achieve complete monitoring of the NS, unlike placing one enclosure on the centre.

The complete NS was installed and balanced regarding rail profile, thus allowing the pantograph skate to render full contact with insulation rods, whilst preventing flashes or overvoltage's [72]. An overhead trolley fitted with a pantograph of the same force with a locomotive travelled between the NS at various speed intervals, generating data. The measured data is transmitted through ThingSpeak™ for the cloud processing, and through the live dashboard for an analysis. To ensure redundancy of communication between the sensors and the cloud, the system on top of the NS was wrapped with aluminium foil to shield the electrical, magnetic interference (EMI) from the overhead wires, though no source of power is present where the fault monitoring is placed [73]. Vibrations and temperature are sampled at various time-intervals and operational conditions, such as speed, temperature, direction, uplifting panto force, and motor tractive forces $F = p/v$.

Figure 3. 1: Installed fault monitoring system on the neutral section

1 - Two enclosures housing sensors installed on NS

2 - Overhead trolley fitted with pantograph

3.2.1.1 Fault monitoring system hardware

Not all available sensors are appropriate in detecting faults on the NS. Below are the components selected to achieve the fault detection process.

Figure 3. 2: Internal circuit of the fault monitoring device

- The ADXL345 accelerometer monitored the vibrations, abnormal applied force, activity/inactivity, and tilt sensing application.
- The non-contact infrared thermometer sensor measures ambient (Ta) and object (To), temperature simultaneously from nearby. The sensor is intended to measure the temperature of the NS return wire clamp under normal and abnormal conditions. The clamp temperature under abnormal condition varied from ambient when a spark/flash was generated from the trains failing to switch-off [74].
- An Arduino microcontroller board is interfaced with accelerometer and non-contact infrared thermometer sensors to collect data, followed by converting the analogue signal into digital. This board is suitable for this experiment because of its low current consumption, smaller size (34mmx18mm) [75].
- The A6 gsm/GPRS module is interfaced with Arduino pro mini to transmit the measured data to the cloud and to send short messages (SMS) as alerts after events are triggered [76].
- A back system powering the circuitry at night is employed in the form of lithium rechargeable batteries.
- A solar charge controller embedded with maximum power point tracking is also employed to charge the batteries and power the entire circuit. Three solar panels are connected to the charge controller to power and charge the lithium-ion batteries.

3.2.1.2 Software's deployed to detect and diagnose failures

The software comprised two parts, indicating Matlab® (building of the machine learning model) and ThingSpeak™ (Cloud computing and data analysis). The acquired data from the experiment is retrieved in a comma-separated values (CSV) format and imported to Matlab®. Based on the fields recorded, the data is clustered into faulty bins. Three methods are employed to evaluate the cluster numbers, indicating elbow method, silhouette and Calinski-Harabasz. Calinski-Harabasz is applied to evaluate the optimal cluster number on the data set, whereas the silhouette plot is employed to determine degree separation of how close each point of a cluster was to point to the neighbouring clusters. These two methods are used to cross-reference the evaluation of clusters since no specific devices could validate unsupervised learning algorithms [78] and [79].

3.2.1.3 The data analysis process

Once the data is generated and stored to the cloud, an analysis of data needed to be completed. The objective is to achieve a qualitative analysis, employing quantitative data measured from sensors in numeric signals. The condition of the NS and pantograph during regular operation is known. Any deviation from the set parameter would trigger alerts. In a case where one of the two objects does not conform, anomaly detection before the pantograph interaction is completed to reduce the impact of the failure. The correlation between the recorded data at various conditions, speed, motor torque and temperature is recorded. The correlation between the speed of the trolley and the frequency response allows the establishment of patterns, whilst testing the hypothesis of simulated data.

Numerical linear correlation coefficient

$$r = \frac{\sum(z_x - z_y)}{n-1} \tag{23}$$

Where Zx equals the score for x and Zy equals the score for y, n- sample size and r-correlation coefficient.

Data analytics is achieved through employing the ThingSpeak™ dashboard data analytics and Matlab® analysis app. Failures of the NS varied; however, the system continuously searched for a pattern or set of groups through employing the analytics feature. The analytics of data must be accurate, dependable and stable to avert the uncertainty and the potential of compromising the data integrity.

3.3 FAULT DETECTION SYSTEM

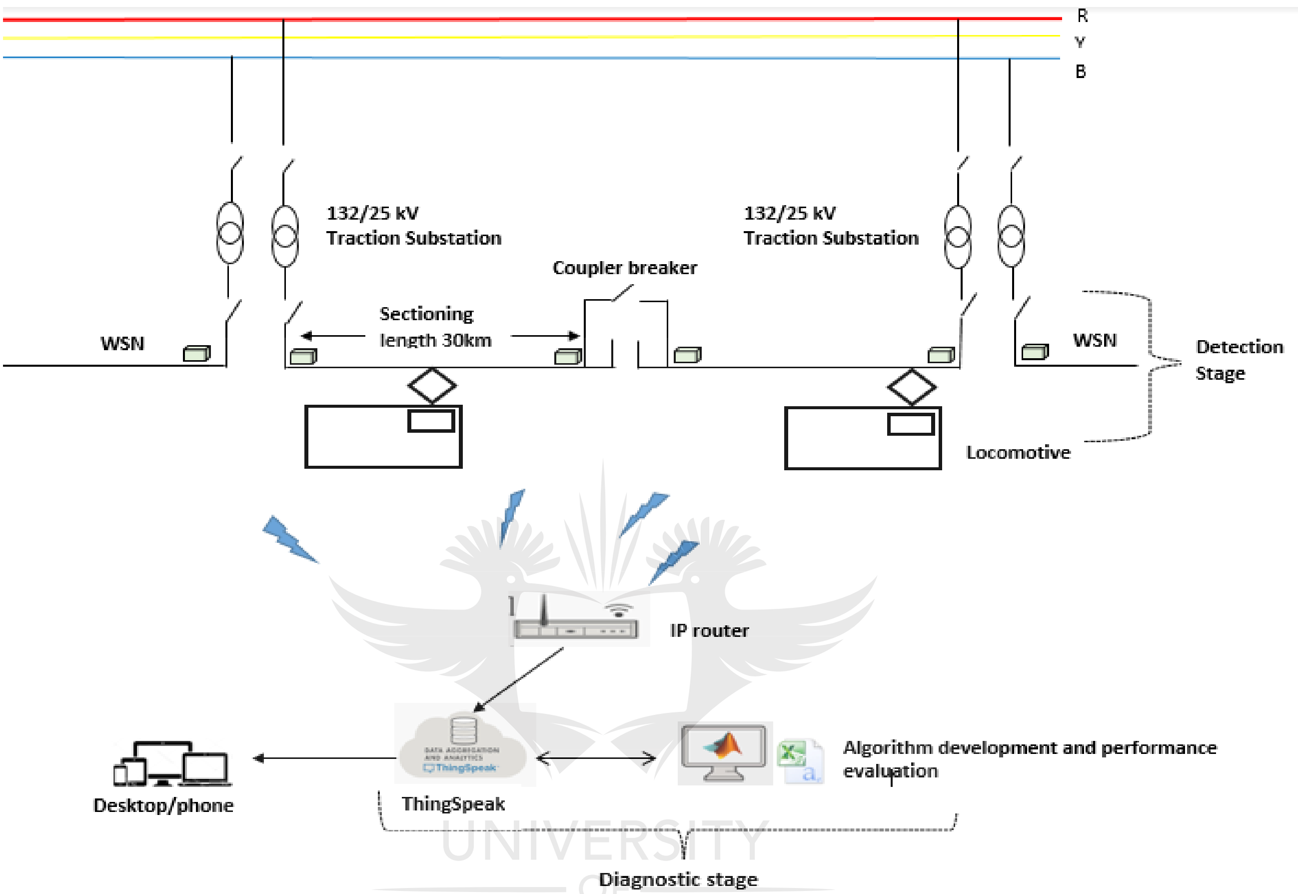


Figure 3. 3: Overview of the data acquisition and processing hardware

The real-world application of an intelligent fault monitoring system, requires a dynamic system, withstanding a harsh environmental impact. The fault detection system comprised three stages, indicating the measuring stage, detection stage and diagnostic stage. An autonomous online fault detecting and diagnosis system is vital for the safety-critical infrastructure for the precise assessment of the fault. This necessitated a device, detecting unreported incidents resulting from mechanical failures by utilising machine learning algorithms for accurate diagnosis.

3.4 PURPOSE OF DIAGNOSIS

The purpose of the diagnosis on the NS faults is to allow the maintenance personnel to plan for maintenance service for the faulty components or the replacement of the components where maintenance is impossible, predicting future failures from the generated patterns. The system is designed to predict future failure and when to execute maintenance. In the higher level, the accelerometers detected the position of the runners concerning the rail where the insulation rods balanced.

3.4.1.1 Alarm/alerts management system

After a fault is detected from the system, an alarm/alert was triggered with a notification through SMS/Tweet to the maintenance personnel. Only upon completion of the three phases, indicating fault detection, fault identification and diagnosis, an alarm/alert would be triggered. This was conducted to prevent false alarms.

Table 3. 1: Diagnostic probability for alarm/alert management

Decision		Fault event	
		Yes	No
Triggered Alarm/Alert	Yes	Correct alarm	False alarm/alert
	No	False alarms	Alarm/No faulty event

3.4.1.2 Background of K-means

In computational intelligence, the K-means algorithm is a clustering device, used to establish hidden patterns in a data set, thereby grouping the data set, based on the similarity. The algorithm aims to reduce the Euclidean distance between the centroids and data set closer to the centroid. K-means is partition-based where K represents the number of clusters, provided the set of data x_i and y_i K-means every data partitions set into clusters. There are numerous applications of the K-means algorithm, applied in other fields, such a fault area detection [80], fault diagnosis [81], research on turn out fault diagnosis method [82] and fault diagnosis based on K-means and PNN [83].

3.4.1.3 Construction of the K-means model

The K-means model is constructed, employing the dataset from ThingSpeak™. There are eight fields (Field 1-8) measured from the pantograph-contact wire interaction. Their fields measured diverse variables from the site, and the data ins transmitted to the cloud for computation and diagnostic. K-means uses distance $d(x_y - y_i)$ to determine the similarity or dissimilarity between the dataset of the detected failures. The complexity of the iterations performed on a large dataset, and the speed of convergence render k-mean computationally attractive compared to other algorithms. K-means was implemented for the objective of grouping the detected faults into clusters. The first K-means is implemented and tested, incorporating Matlab® (Appendix A2). After the testing phase, the algorithm is evaluated to improve its efficiency and robustness to outliers.

Algorithm: K-means

Input: M, K where M= set of measured data and K= integer

Output: K clusters

Require $M \neq \emptyset, K > 0$

Procedure Generate Cluster (k-fold)
    Initialise K random Centroids
    repeat
        for all Instance i in M **do**
            shortest ← 0
            membership ← null
                for all Centroid c **do**
                    dist ← Distance(c)
                    if dust < shortest **then**
                        shortest ← dist
                        membership ← c
                    end if

end for
end for
Recalculate Centroids(c)
Until convergence
end procedure

ThingSpeak™ generated eight data fields from the wireless sensors; the data originated in the form of a raw numerical value. The data is unstructured and unfiltered; computational analytics are performed live, whilst data trickled. In a case where the set limits were exceeded, an alert is activated instantaneously. The following steps are conducted in online detection, employing K-means.

- record parameter from sensors (Ta, To, AccX, AccY, AccZ, Angle X, AngleY, AngleZ)
- the dataset is recorded into respective cells
- computed K-means and SVMs
- alerts triggered, attributable to abnormalities detected

Table 3. 2: Parameter detected and selected for K-means clustering

Parameters	Time	Recorded field values (1-8)
Ambient temperature (Ta)		
Object temperature (To)		
Acceleration X		
Acceleration Y		
Acceleration Z		
Angle X		
Angle Y		
Angle Z		

3.4.1.4 Construction of support vector machines

An SVMs based classifier is employed to detect and classify locomotive pantographs, based on the number of interactions on the NS. An SVM based classifier needs to be trained through two data sets, indicating training data and testing data. An SVM is also implemented for the objective of classifying and predicting the locomotive pantographs number, employing the linear kernel function. An SVM data set is trained and tested, employing Matlab® (see Appendix A3).

Algorithm: Training an SVM

Require: $x, y, and\ z$ loaded with trained labelled data $\alpha \Leftarrow 0$ or $\alpha \Leftarrow$ trained SVM
$C \Leftarrow 100$ (training data)
repeat
    for all (x_i, y_i, z_i); (x_j, y_j, z_j); do
        optimize decision boundaries $\alpha_i\ and\ \alpha_j$
    end for
  until no changes in α or other resource constraint are met
Ensure: Retain only the support vectors $(\alpha_i > 0)$

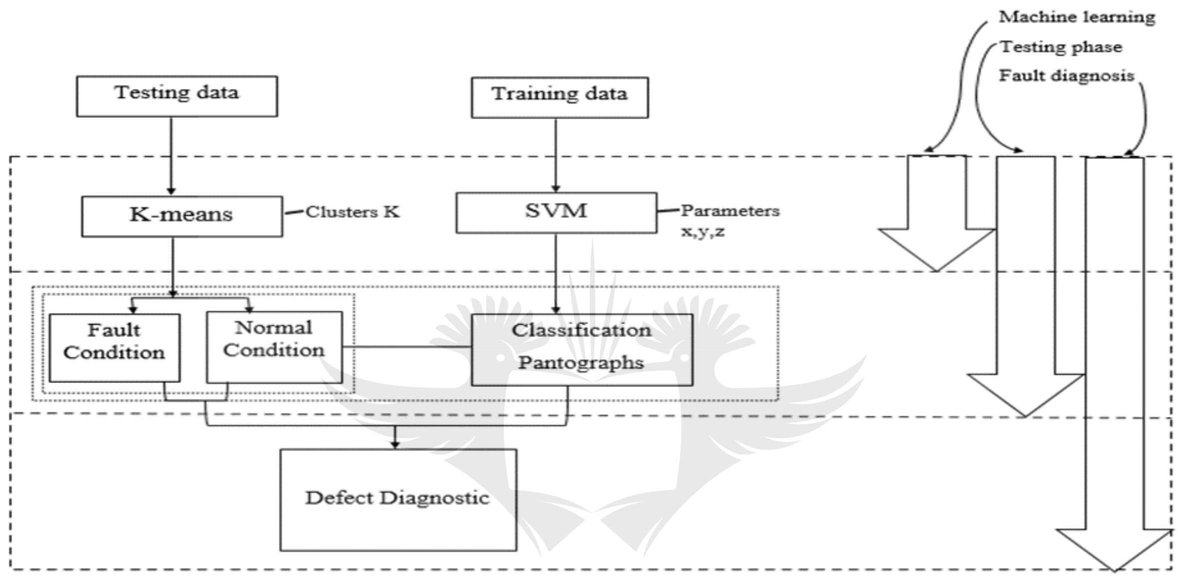


Figure 3. 4: Fault diagnosis flow chart for K-means and support vector machines

3.4.1.5 Fault diagnosis method-based K-means and the support vector machine

Classifying data is one of the challenges in machine learning. The flow chart for fault diagnosis in Figure 3.3, encompasses algorithms K-means and SVM; the K-means is responsible for clustering the dataset, based on the condition detected. Conversely, the SVM classifies the pantographs of the locomotives. SVM parameters x,y,z of the model are trained through the training data fields. The testing phase for fault detection holds set limits. Where the limits are exceeded, an alarm is triggered in real-time. The defect diagnosis testing data were extracted from the measurement fields. The model is trained, employing the parameters to predict the defects. Various faults obtained from the training data are used to validate the correctness of the algorithm and its prediction.

3.5 CONCLUSION

This chapter presented the methodology for data acquisition and fault diagnosis. The algorithms employed to detect anomaly and diagnosis are evaluated. The development of the framework contributed to the fault detection of an NS fault on the railways. Validity and suitability of the quantitative results are further discussed in detail in Chapter 4. The interpretation of results is outlined with the values of the numerical input measurements. The correlation between the speed of the trolley and the frequency response allowed establishing patterns and assessing the hypothesis of simulated data.

CHAPTER 4

MACHINE LEARNING DIAGNOSTIC AND PATTERN ANALYSIS

4.1 INTRODUCTION

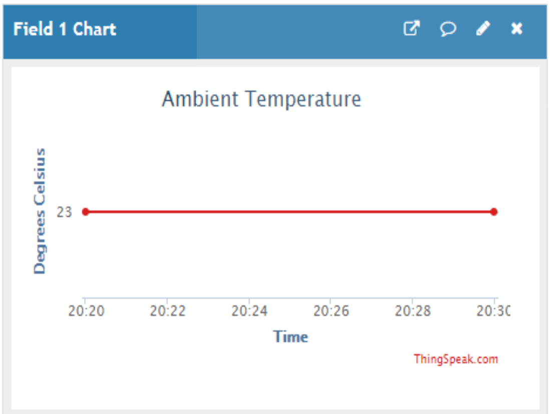
Chapter 3 reflects the development framework of the fault monitoring system on the NS, including the primary components (detection, diagnosis, and algorithm intelligence). The framework and circuitry are put in practice where the results are validated, and the diagnosis evaluated. The results from onsite simulations are presented, employing ThingSpeak™ for online analysis and visualisation.

Clustering and classification are achieved, employing Matlab® from the data generated from the ThingSpeak™ file. This section elaborates on quantitative measurements from the pantograph-contact wire interaction, employed to achieve qualitative results. These results are used to describe the qualities of the NS fault detection.

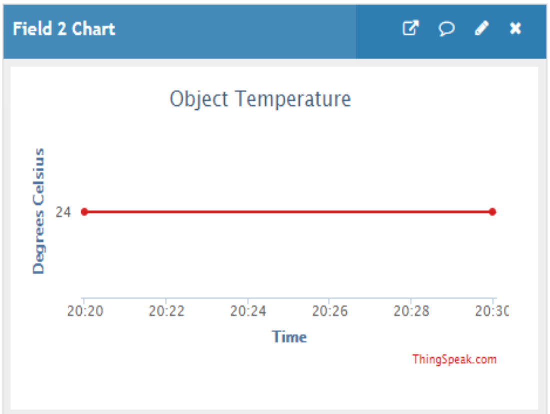
4.2 THINGSPEAK™ ONLINE ANALYSIS AND VISUALISATIONS

4.2.1 Ambient and object temperature

The first two measurements are ambient temperature and object (return wire and parallel clamp). The significance of the temperature is that it allowed the system to differentiate between mechanical failure and an electrical fault from incidents. The online fault monitoring system operates 24 hrs to determine the temperature trends. The change in temperature from the object is minimal under normal conditions, unlike faulty conditions where the object temperature raised exponentially, then dropped after cooling.

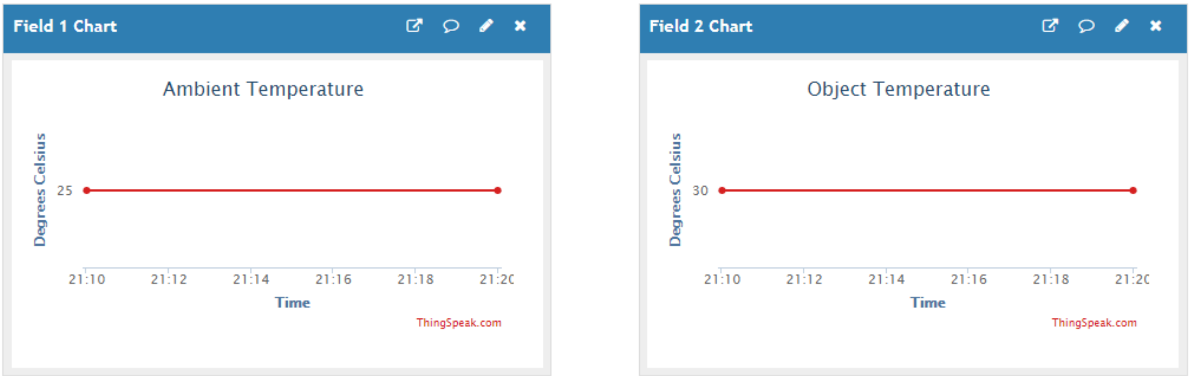


(a)



(b)

Figure 4.1: Online (a) ambient and (b) object temperature readings during normal conditions

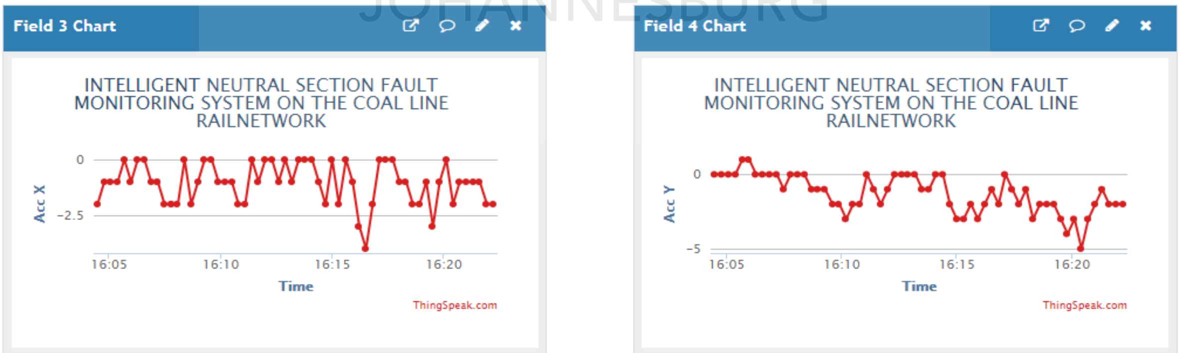


(a) (b)

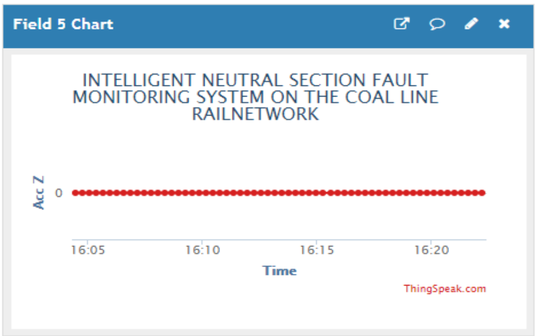
Figure 4.2: Online (a) ambient and (b) object temperature readings during faulty conditions

Under faulty conditions, the object temperature is set to trigger an alarm, reaching 30°C and above for this experiment (Figure 4.2). Under faulty condition, locomotive failing to switch-off, the power dissipated $E = v^2/(R \times t)$ as result instigated temperature increase on both return wire and parallel clamp. The increase in heat is mainly produced by the fault currents, that triggered alarm that is sent through SMS and Twitter with the exact temperature reading from when the fault occurred. Under abnormal conditions in the case where the locomotive failed to switch-off, a spark is generated and recorded by a sensor to distinguish from failing when unbalanced. The failure is said to be electrical caused when the spark is generated resulting from return wire and balancing droppers being burnt-off.

4.2.2 Vibration acceleration for X, Y and Z-axis



(a) (b)

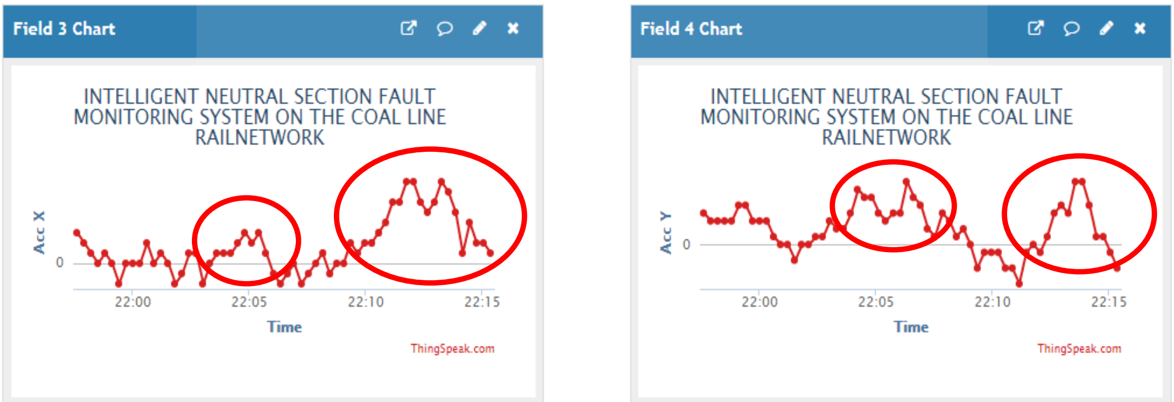


(c)

Figure 4.3: Vibration acceleration for (a) Acc-X, (b) Acc-Y and (c) Acc-Z before the pantograph made contact with the neutral section

This section is divided into two phases. In the first phase of the experiment, the device is installed and operates independently to measure and record without any external influence, to establish the behaviour of accelerometer readings for X, Y and Z.

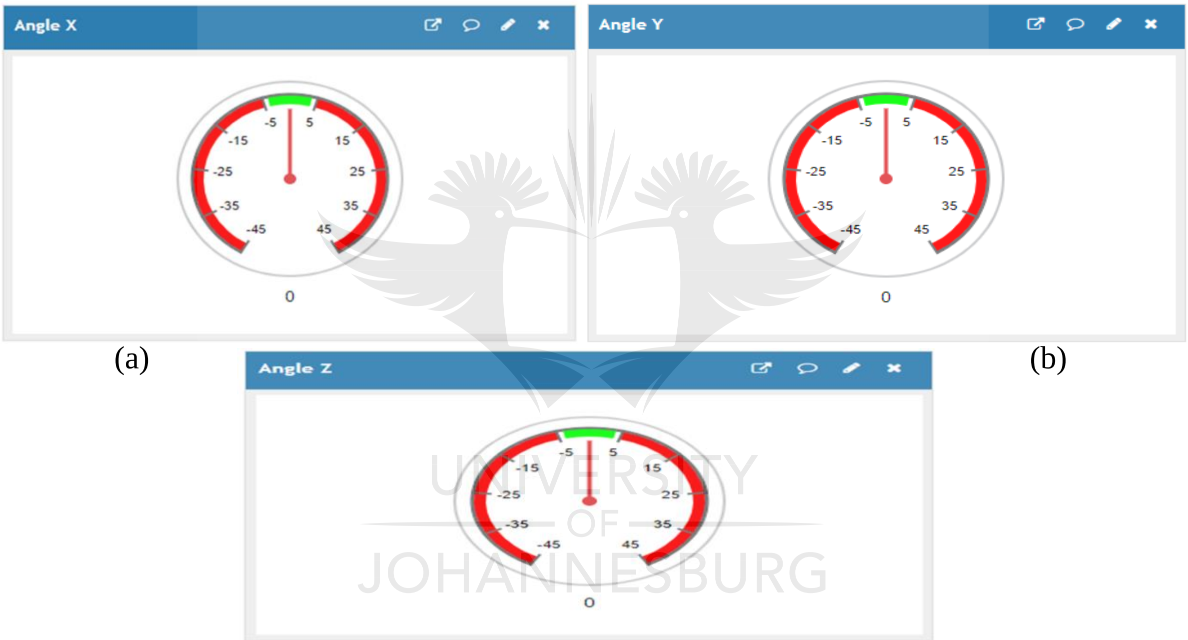
The second phase of the experiment allows the overhead machine vehicle to operate at various speed intervals, such as 15km/h, 30km/h, 45km/h, and 60km/h to assess the behaviour pattern of the accelerometer (X, Y & Z). The starting tractive force of the overhead trolley is high 370kN for Main Line 1 as the trolley headed towards Ermelo, whereas heading towards the Vryheid side tractive force is 310kN. The direction and slope of the rail track influenced the tractive force of the trolley, resulting in further tractive force used to accelerate trolley speed to 60km/h. It can be observed from Figure 4.3 that with a lack of interaction between the contact wire and pantograph, measured readings are present from the X and Y- axis, ranging from 0 to -5m/s² stemming from external wind forces, exerted on overhead wires.



(a) (b)

Figure 4.4: Vibration acceleration for (a) Acc-X and (b) Acc-Y after the pantograph touches the neutral section with significant changes in vibration acceleration

Figure 4.4 presents the vibration acceleration for X and Y- axis, after the pantograph passes through the NS, with significant changes in vibration acceleration after the abnormal fault as shown on figure 4.4 (a) and (b). The contact wire experiences forced vibrations, resulting from the force exerted by the pantograph. Simulations through various speed intervals are employed to estimate the peak of the NS oscillations. These are used to determine equipment failure from normal conditions. Various vibration accelerometer intermittently, authorised the algorithm to predict NS runner failure. This benefits the network availability by scheduling maintenance for improved safety. To quantitatively explain the trend of the simulation, the change in speed held a direct influence on the detected vibration; it is observed, peak vibrations at higher speed (60km/h) with 310KN tractive force was $x=-60 m/s^2$ ad $y=40 m/s^2$ on figure 4.4 (a) and (b).

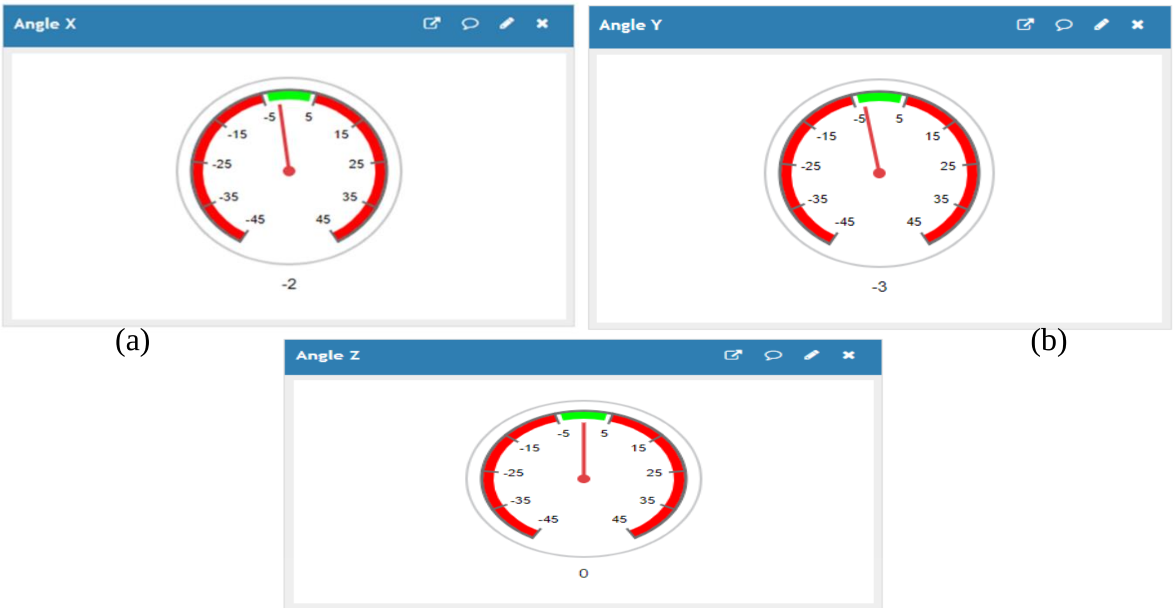


(a) (b) (c)

Figure 4.5: Tilt angles for (a) angle X, (b) angle Y and (c) angle Y under normal conditions

4.2.3 Vibration angle for X, Y and Z

In Chapter 2, the placement and orientation of the enclosures housing the accelerometers are extensively discussed; however, the axial tilt (pitch α and roll) of the 3-axis accuracy rests on the alignment of the sensitive axes. Under normal conditions concerning rail orientation, the 3-axis read zeros tilt angles without the exerted force from the pantograph. The set limits are -5° to +5°, allowing the external forces exerted by wind/rain/hail not to trigger a false alarm during normal conditions [83] and [84].



(a) (b) (c)

Figure 4.6: Tilt angles for (a) angle X, (b) angle Y and (c) angle Z under abnormal conditions

Experimental results indicate that the tilt angles values after the locomotive passed through the NS changes, attributable to the oscillation caused by the vibration of the pantograph into the contact wire. The system is designed to trigger an alarm when the tilt angle of 3-axis rises above the set limits. The latch time for triggering alerts is 30 seconds; in every 30-second interval, the system would evaluate the NS tilt condition and trigger alert in an abnormal condition. The system is developed to detect when the NS arc runners and balancing droppers fail with the tilt angle established outside the set limits. The tilt and orientation of the system allows the device to detect failures resulting from mechanically faults. This gives accurate root cause of the failure instead assuming electrical and mechanical are of same group.

4.2.4 Error analysis

The intelligent fault monitoring system is exposed to harsh environmental conditions, such as wind and rain. It is also subjected to speed change and pantograph force upliftment. Through the experiments, external influence and gyroscope drift resulted from accelerometer sensors from forced forces exerted on the NS and accelerometer sensitivity drifts. The following parameters are identified as influencing the accelerometer behaviour:

- overhead machine vehicle speed
- contact wire height/ruling height

- contact wire force
- pantograph position
- pantograph upliftment force
- condition of track
- wind speed
- rain/hail

Figure 4.7: Real-time alerts for detected failures through Twitter

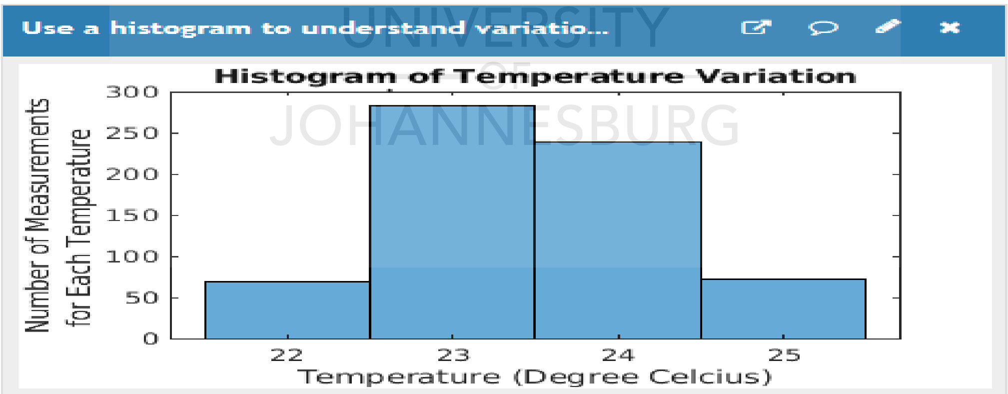


Figure 4.8: Online analysis for histogram of temperature variation

4.3 MACHINE LEARNING ALGORITHM through MATLAB®

4.3.1 Applying the K-means model

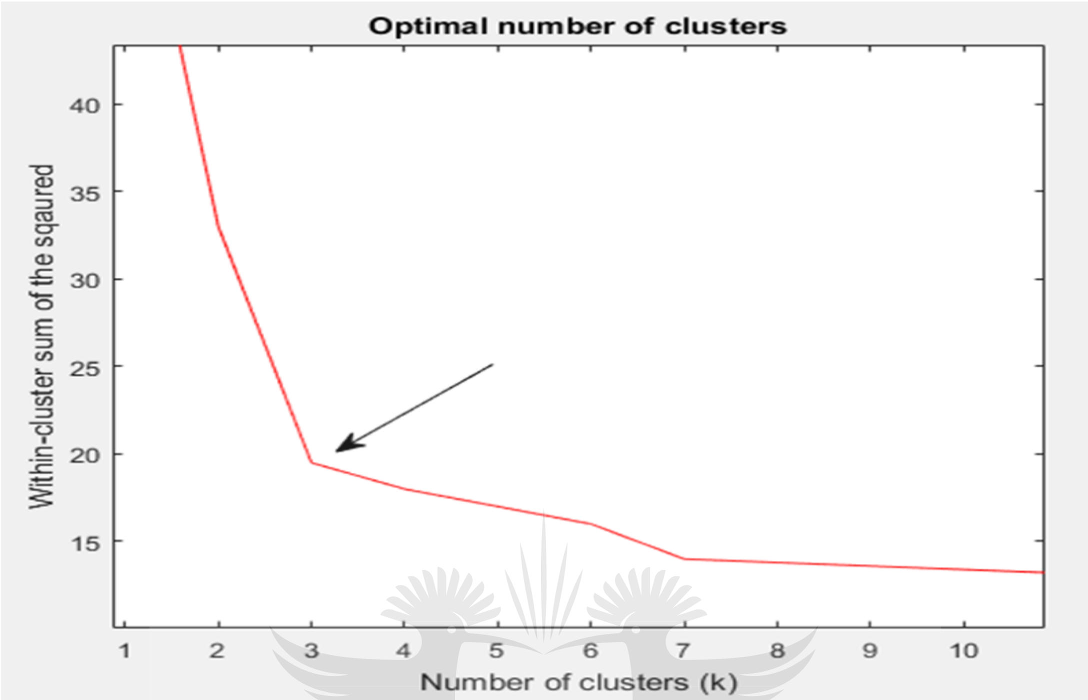


Figure 4.9: Optimal number of clusters using elbow method

The experimental results recorded into CSV file from the cloud are imported into Matlab® were plots and analysis are performed. Figure 4.9 shows the optimal number of clusters were k equals 3 were the graphs begins to flatten, precise number of clusters is essential for accurate clustering. K-means is computed for different values of k ranging from 1 to 10 clusters were for each value of k within-cluster sum of the squares (wss) is calculated. Results of the wss is plotted against the number of clusters value (1-10). The optimal number of cluster is 3 were the graph begins to bend/flatten.

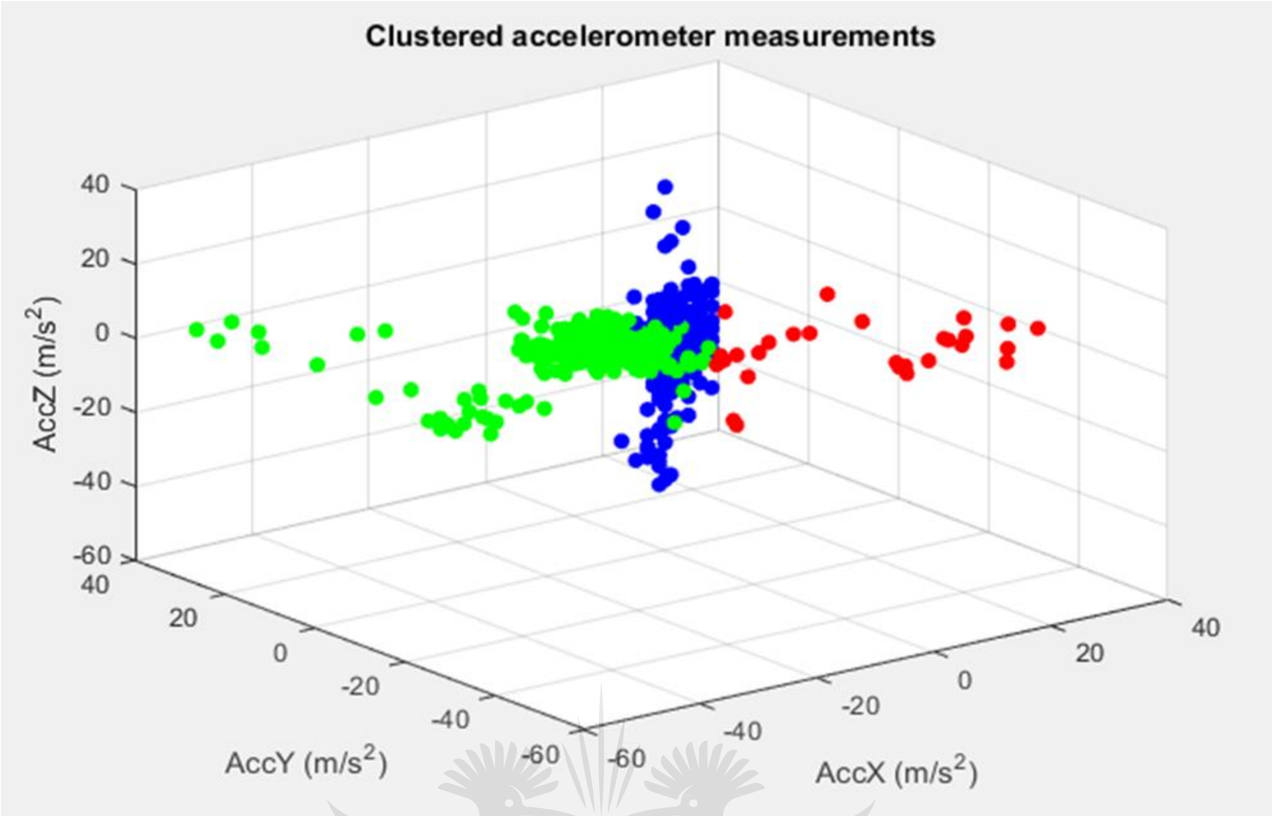


Figure 4.10: Clustered accelerometer events were locomotive passing through the NS

The figure 4.10 shows a 3D scatter plot of clustered accelerometer measurements (X, Y & Z axis) where the locomotive passes through the NS and are automatically represented by three different colours. The blue colour represents the detected pantograph events where the locomotive pantographs were interacting with the NS whereas the green colour represents contact wire oscillations after the pantograph past the NS. The contact wire oscillates because of the exerted force by the pantograph in motion. The oscillation of the contact wire is also influenced by the speed of the locomotive. Lastly the red colour represents the excessive winds experienced during the experiment. All these events are recorded through the experiment and as result are represented by different cluster colour using k-means. Clustering of the events using k-means proved to be feasible on the NS fault monitoring by grouping the events.

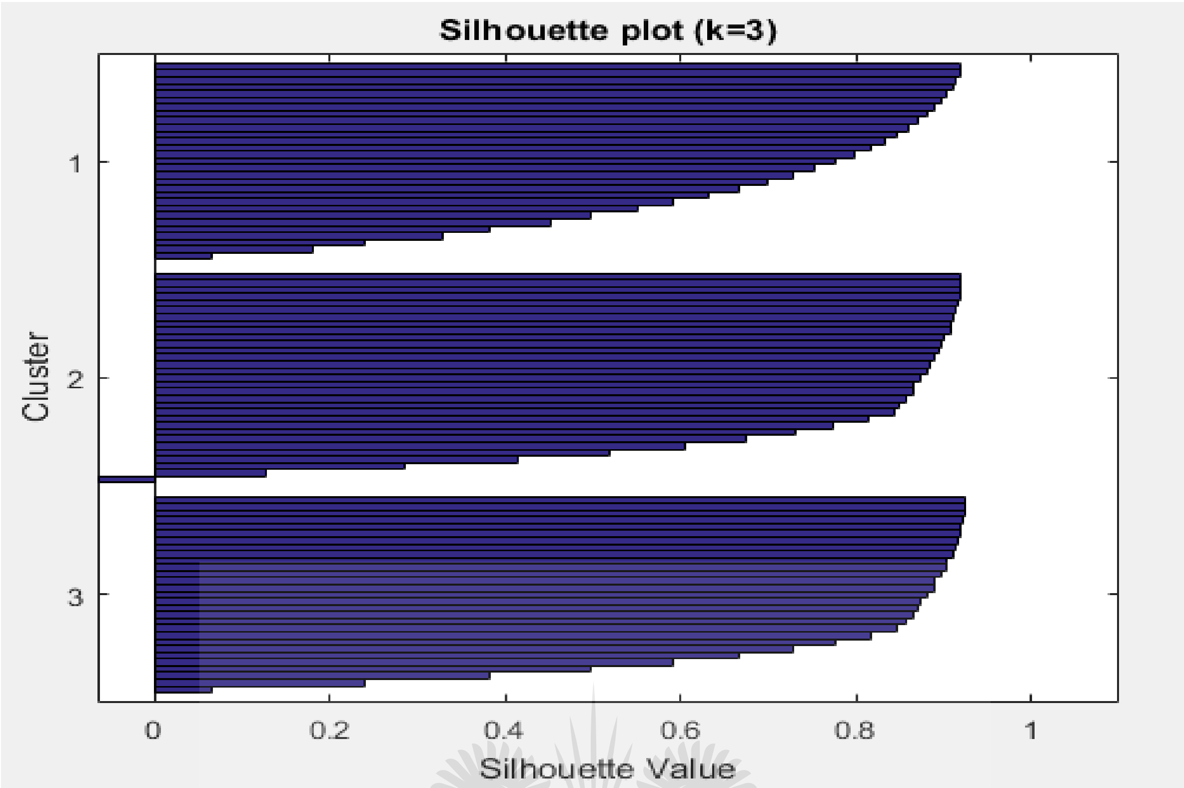


Figure 4.11: Silhouette plot for K-means clustering (k=3)

The silhouette diagram depicted in Figure 4.11 indicates the clusters separated from the dataset where k equals 3. The thickness and value of the silhouette coefficient shows correct k-clusters, indicating the points distant from neighbouring clusters [85]. The temperature and vibration acceleration respectively hold three clusters k=3.

```
EvaluateK =

  CalinskiHarabaszEvaluation with properties:

    NumObservations: 89
         InspectedK: [1 2 3]
    CriterionValues: [NaN 260.7190 341.7839]
           OptimalK: 3
```

Figure 4.12: Calinski-Harabasz evaluation index (k=3)

K-means was chosen as the clustering algorithm. Calinski-Harabasz was employed to evaluate the optimal cluster figure (k) containing the data, derived from the silhouette plot. The observation value was iterated 89 times, and the results confirmed that the optimal choice of k is three (3).

4.3.2 Classification using the support vector machine

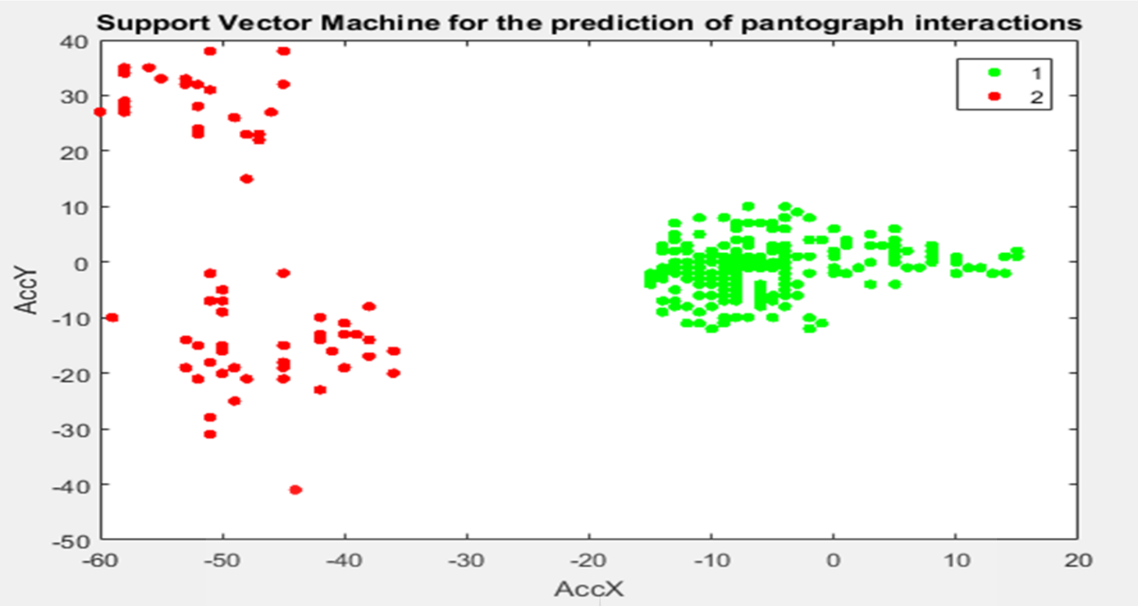


Figure 4.13: SVM classifier for the prediction of locomotive interactions

Figure 4.13 shows gscatter plot of two classes represented by different colours, class A equals red and class B equals green. The methodology is implemented on the experimental dataset collected from pantograph-contact wire simulation tests. The classification learner app is used to train and select the best classifier for the locomotive passes were all SVM classifiers are used to train and test the model, with input predictors (acceleration recordings) and response as labels. 80-20 train-test ratio is used to generate and verify the SVM classifier model. Cross-validation $(k - fold\ crossval,' k', p)$ of the training was inaugurated to validate data feature and pattern accuracy, this optimised the SVM parameters [86-89]. With the experimental dataset, the linear kernel SVM is used to train and separate the loco pantographs passes from the events recorded with the accuracy of 100%. Class A from figure 4.13 indicates the locomotive pantographs recorded while the locomotive traversing at the NS at different speed intervals (15km/h, 30km/h, 45km/h, and 60km/h) whereas Class B are events detected (contact wire oscillations after pantograph passed the NS and excessive winds) Other SVM classifiers were tested and the best classifier model with higher accuracy and lower error is selected as linear kernel SVM as shown on table 4.1. The training data expansion is recommended to improve the SVM classifier for pantographs; large training sets are not readily available to model and simulate faults under measured conditions.

Table 4. 1:Accuracy of each classifier trained

Classifier	Accuracy	Error	Training time
Linear SVM	100%	0%	19,54sec
Quadratic SVM	99,4%	0,6%	35,74sec
Cubic SVM	99,4%	0,6%	233,6sec
Fine Gaussian SVM	90%	10%	10,38sec
Medium Gaussian SVM	99,4%	0,6%	11,65sec
Coarse Gaussian SVM	89,1%	10,9%	10,35sec

4.4 CONCLUSION

This chapter presented experimental results achieved through ThingSpeak™, machine learning diagnostics and pattern analysis using K-means and SVM classifier. Three tools were employed to evaluate the optimal number of clusters for k-means. The classification learner app was utilised to determine the best SVM classifier were the effectiveness of the SVM classifier trainer was analysed. Linear kernel SVM proves to be good on prediction and can be further for fault analysis. Unsupervised learning is demonstrated to be feasible on the railway overheads being able to detect and classify events accordingly.

CHAPTER 5

CONCLUSIONS

5.1 INTRODUCTION

This chapter presents the study summary and conclusion presented on the intelligent NS fault monitoring system. A proposal for further research and applying the system in practice is also summarised.

5.2 CONCLUSION

The NS is a critical component of the overhead infrastructure, particularly on the 25kV AC system. The effective operation of the NS ensures high network availability, and safe train passage by minimising incidents with impacts and lowering maintenance costs. Unpredicted failures lead to train services' shutdown or suspension. The results are revenue losses, influencing the entire value chain negatively. A system is required, detecting failures and diagnosis failure from the original state.

Chapter 1outlines the study aims and objectives, were the framework for fault monitoring to detect and classify locomotives vibrations is developed, differentiate and grouping of events is also achieved using the two algorithms k-means and support vector machine.

Chapter 2 reviews traditional methods employed to detect and distinguish faults. No established intelligent system could be identified that detects a failure, whilst predicting failures from the original state. This system identified in the study aims to address the shortcoming of detecting faults unreported by train drivers, whilst monitoring the condition of the entire NS before and during operation.

Chapter 3 elaborates on a proposed method to develop a framework, significantly contributing to monitor the device before and during the operation. The prevailing methods employed to detect failures are based on alarms systems where certain threshold exceeded the system shutdown through the equipment's electrical control in the control station. A model-based system was proposed to detect and diagnose failures. With the collected data, maintenance personnel can predict the timeous execution of maintenance.

Fault detection through ThingSpeak™

- The process and methods (hardware and software) employed to acquire data for the system was proposed and implemented.

- The methodology for fault detection of abnormal events was implemented and tested, employing ThingSpeak™. Unreported hidden faults and subtle change in the condition of the NS insulation rods were exposed.
- Chapter 3 and 4, respectively propound fault detection and classifier algorithms.
- Two techniques were employed to detect and predict the pantographs events. Both these techniques were evaluated using data generated from ThingSpeak™.

Chapter 4 presents the practical implementation and testing of the system, conducted through ThingSpeak™ and Matlab®. Testing of the system generated vital discoveries of the NS behaviour pattern. It was observed that the NS was influenced by the auto-tension cantilevers as opposed to the spring tension. A slight change in the condition of the NS arc runners and position are indicated during temperature change. When the OHTE trolley traversed, the angular position changed, attributable to the force exerted by the pantograph. The system generated noise (excessive winds) under the no-testing phase; the accelerometer gyroscope drifted during pantograph and contact wire interactions.

This study emphasises on features of fault detection and classification, vital to the efficient operation of train services and monitoring industry condition. The research conducted aims to contribute to earlier detection of abnormal events to minimise frequent failures, whilst increasing the lifespan of the asset condition.

5.3 FURTHER RESEARCH

The study substantiated that the SVMs and K-means techniques may be used as fault detection and diagnostic devices for NS fault monitoring in the railways. Further research and developments can be conducted to contribute to the fault monitoring of overhead railway infrastructures.

The study identified crucial concerns, indicating random noise, gyroscope drift and electromagnetic interference (EMI) from 25kV AC when switched-on during train operations. The accuracy of sensor measurement is crucial in precise fault diagnosis, increased asset utilisation, whilst improving user quality experience. The device under work permit (25kV AC disconnected from the traction substation feeder switches) usually functioned, with interferences of measured results from the site. Vibrations and angles X, Y, Z produced incorrect values under test simulations, ranging from 1023 and 1034 m/s².

The temperature readings provided the same readings, ranging from 1023 and 1034 °C. A proposed solution to this challenge is a Kalman filter that could be used to reduce the noise and compensate for the accelerometer gyroscope drift. The Kalman filter also called a linear quadratic algorithm, employing the measurement of the accelerometer over time, comprised noise and outliers to filter data and limit the threshold of variables over each timeframe [90-91]. The Kalman filter is one of the most used model-based algorithms, attributable to its high accuracy and excellent real-time performance on signal processing.

Harsh environmental interference and swinging auto-tension overlap cause the noise from the accelerometers. Another addition to the proposed solution filtering output signal of gyroscope directly from the circuitry is employing adaptive filtering. This filter uses the Allan variance device to analyse the entire noise from the output signal of the gyroscope. Another extension to the proposed solution is to model the EMI filter that can kerb, or limit interferences caused by the single-phase overhead wire, running on the top side of the device. Receptors (devices for online monitoring) are susceptible to noise, emitted from the power source or transmission lines, running closer to the device.

5.4 APPLYING THE SYSTEM IN PRACTICE

Before the intelligent NS fault monitoring system could be implemented in the entire coal line, it needs approval from the Technology Management Department. This approval assisted significantly in understanding the NS behaviour failure patterns and maintenance philosophy required from the various regions. This particularly includes Ion and Manganese, where the line voltage and train dynamics differs from the coal line. The online fault detection and diagnosis system should significantly contribute to the driverless train operation (Automatic Tran Operation), sending NS condition to the base station where the algorithms are deployed. This could ensure computing autonomously to stop the locomotives from traversing into a damaged or defective area.

Specific research methods were not applied in the field of fault detection and diagnosis of NS in the railways. First, the proposed method used to detect failures on the NS might not indicate anomalies detected, based on the data generated. Extensive simulations need to be executed to produce massive data where the algorithms could be trained and assessed, employing various failure data patterns. The automated fault detection and diagnosis was based on the data generated from the site, using the overhead trolley fitted with the pantograph and the data from the NS manufactures. These methods ensured that limits were set for abnormal failures modelled to allow the algorithms to be trained and evaluated. The SVM and K-means were proposed as a mean of quantitatively and qualitatively assessing the failure modes and diagnosis, ascribed from the generated data.

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APPENDIX A: LIST OF CODES

APPENDIX A1: FAULT DETECTION

The fault detection of the NS incident was implemented using Arduino interfaced with ThingSpeak™. ThingSpeak™ receives data constantly, which allows cloud computing and online visualisation.

A1. Implementation of the fault detection using ThingSpeak™ IDE

```
#include <Wire.h>

#include <MPU6050_tockn.h>

#include <Adafruit_MLX90614.h>

#include <mpu6050>

MPU6050 mpu6050(Wire);

Adafruit_MLX90614 mlx = Adafruit_MLX90614();

void WiFiConfig();

void SendToThingSpeak™(int AmbientTemp, int ObjectTemp, int GetAngleX, int GetAngleY, int GetAngleZ, int GetAccX, int GetAccY, int GetAccZ);

int GetTempValue(bool Status);

int GetAngle(char GetAngleType);

int GetAcc(char GetAccType);

void setup() {

 Serial.begin(115200);

 Serial.println("Adafruit MLX90614 test");

 mlx.begin();
```

```
 Wire.begin();
 mpu6050.begin();
 mpu6050.calcGyroOffsets(true);
 WiFiConfig();
}
void loop() {
 SendToThingSpeak™(GetTempValue(true), GetTempValue(false), GetAngle('X'), GetAngle('Y'), GetAngle('Z'), GetAcc('X'), GetAcc('Y'), GetAcc('Z'));
}
/******************************************************************************
**************************************************************/
void WiFiConfig()
{
 Serial.print("AT+RST\r\n");
 delay(2000);
 Serial.print("AT+CWMODE=1\r\n");
 delay(4000);
 Serial.print("AT+CWQAP\r\n");
 delay(4000);
 Serial.print("AT+CWLAP\r\n");
 delay(5000);
 Serial.print("AT+CWJAP=\"HUAWEI-C6E4\",\"00315789\"\r\n");
```

```
 delay(4000);

 Serial.print("AT+CIPMUX=1\r\n");

 delay(4000);

 Serial.print("AT+CIPSTART=0,\"TCP\",\"184.106.153.149\",80\r\n");

 delay(2000);

}

/*****************************************************************************
**********************************************************/

void SendToThingSpeak™(int AmbientTemp, int ObjectTemp, int GetAngleX, int GetAngleY, int GetAngleZ, int GetAccX, int GetAccY, int GetAccZ)

{

 String InitSent = "AT+CIPSEND=0,";

 String APIKey = "GET https://api.ThingSpeak™.com/update?api_key=5B5DX5TDOPD2MOS3";

 String APIField1 = "&field1=";

 String APIField2 = "&field2=";

 String APIField3 = "&field3=";

 String APIField4 = "&field4=";

 String APIField5 = "&field5=";

 String APIField6 = "&field6=";

 String APIField7 = "&field7=";

 String APIField8 = "&field8=";
```

```
String GetAmbientTempValue = String( AmbientTemp);

String GetObjectTempValue = String(ObjectTemp);

String GetAngleXValue = String( GetAngleX);

String GetAngleYeValue = String(GetAngleY);

String GetAngleZValue = String(GetAngleZ);

String GetAccXValue = String (GetAccX);

String GetAccYValue = String (GetAccY);

String GetAccZValue = String (GetAccZ);

APIKey += APIField1 + GetAmbientTempValue + APIField2 + GetObjectTempValue + APIField3 + GetAngleXValue + APIField4 + GetAngleYeValue + APIField5 + GetAngleZValue + APIField6 + GetAccXValue + APIField7 + GetAccYValue + APIField8 + GetAccZValue;

int GetNumberOfChar = APIKey.length() + 2;

//Serial.println(GetNumberOfChar);

//Serial.println(APIKey);

Serial.print("AT+CIPMUX=1\r\n");

delay(3000);

Serial.print("AT+CIPSTART=0,\"TCP\",\"184.106.153.149\",80\r\n");

delay(3000);

Serial.print(InitSent);

Serial.print(GetNumberOfChar);

Serial.print("\r\n");
```

```
 delay(2000);
 Serial.print(APIKey);
 Serial.print("\r\n");
 delay(1000);
}
void SendToThinkSpeak2(bool SelectPort)
{
 if (SelectPort == true)
 {
 Serial.print("AT+CIPSTART=\"TCP\",\"184.106.153.149\",\"80\"\r\n");
 delay(3000);
 Serial.print("AT+CIPSEND=102\r\n");
 delay(1000);
 Serial.print("GET https:// GET
https://api.ThingSpeak™.com/update?api_key=5B5DX5TDOPD2MOS3&field1=74);
 //Serial.print((char)0x1A);
 Serial.print("\r\n");
 }
 else if (SelectPort == false)
 {
 mySerial.print("AT+CIPSTART=\"TCP\",\"184.106.153.149\",\"80\"\r\n");
```

```
 delay(3000);

 mySerial.print("AT+CIPSEND=102\r\n");

 delay(1000);

 mySerial.print("GET https:// GET https://api.ThingSpeak™.com/update?api_key=5B5DX5TDOPD2MOS3&field1=74);

 // mySerial.print((char)0x1A);

 mySerial.print("\r\n");

 }

}

void GPRS_GMS_Setting(bool SelectPortCon)

{

 if (SelectPortCon == true)

 {

 Serial.print("AT+CIPSHUT\r\n");

 delay(3000);

 Serial.print("AT+CIPMUX=0\r\n");

 delay(3000);

 Serial.print("AT+CGATT=1\r\n");

 delay(3000);

 Serial.print("AT+CSTT=\"myMTN\",\"mtnwap\",\"mtnwap\"\r\n");

 delay(3000);
```

```
Serial.print("AT+CIICR\r\n");

delay(3000);

Serial.print("AT+CIFSR\r\n");

delay(3000);

}

else if (SelectPortCon == false)

{

mySerial.print("AT+CIPSHUT\r\n");

delay(3000);

mySerial.print("AT+CIPMUX=0\r\n");

delay(3000);

mySerial.print("AT+CGATT=1\r\n");

delay(3000);

mySerial.print("AT+CSTT=\"myMTN\",\"mtnwap\",\"mtnwap\"\r\n");

delay(3000);

mySerial.print("AT+CIICR\r\n");

delay(3000);

mySerial.print("AT+CIFSR\r\n");

delay(3000);

}
```

```
/****************************************************************************
************************************************************/
int GetTempValue(bool Status)
{
 if (Status == true)
 {
 return ( (int)mlx.readAmbientTempC());
 }
 if (Status == false)
 {
 return ((int)mlx.readObjectTempC());
 }
}
/****************************************************************************
************************************************************/
int GetAngle(char GetAngleType)
{
 mpu6050.update();
 if (GetAngleType == 'X' || GetAngleType == 'x')
 {
 return ((int)mpu6050.getAngleX());
 }
```

```
if (GetAngleType == 'Y' || GetAngleType == 'y')

{

return ((int)mpu6050.getAngleY());

}

if (GetAngleType == 'Z' || GetAngleType == 'z')

{

return ((int)mpu6050.getAngleX());

}

/****************************************************************************
************************************************************/

int GetAcc(char GetAccType)


mpu6050.update();

if (GetAccType == 'X' || GetAccType == 'x')

{

return ((int)mpu6050.getAccX());

}

if (GetAccType == 'Y' || GetAccType == 'y')

{

return ((int)mpu6050.getAccX());

}
```

```
if (GetAccType == 'Z' || GetAccType == 'z')

{

return ((int)mpu6050.getAccX());

}
```

APPENDIX A2: CLUSTERING USING K-MEANS

The K-means algorithm described in Chapter 4 and 5, is implemented using Matlab® offline and ThingSpeak™ for online analysis. The following code is used to group the data based on the similarities using Euclidean distance.

A2. Implementation of the K-means clustering on Matlab®.

```
data=xlsread('feeds.xlsx');

InputData=data(:,1:8);

scatter3(InputData(:,3),InputData(:,4),InputData(:,5));

rng(1);

[IdCluster,Centroid]=K-means(InputData,3);

scatter3(InputData(:,3),InputData(:,4),InputData(:,5),IdCluster,'bgrm','x*o^')

hold on

plot3(Centroid(:,3),Centroid(:,4),Centroid(:,5),'x','LineWidth',4,'MarkerEdgeColor','k',
'MarkerSize',15)

axis auto;

xlabel('AccX (m/s/2’));

ylabel('AccY (m/s/2));

zlabel(‘AccZ (m/s/2’));

title('Clustered accelerometer measurements’);

EvaluateK=evalclusters(InputData,'K-means','Calinski-Harabasz','KList',[1:2])
```

APPENDIX A3: FAULT DIAGNOSIS AND CLASSIFICATION SUPPORT VECTOR MACHINE

SVM was implemented through Matlab® offline from the data generated from ThingSpeak™. The SVM consisted of two features, train and test data. The features and patterns were extracted to train the system to predict and diagnose events.

A3. Implementation of the fault diagnostic and classification.

```
data=xlsread('feeds.xlsx');
InputData=data(:,1:9);
gscatter(InputData(:,3),InputData(:,4));
rng(1);
[Train,Test]=crossvalind('HoldOut',group,p);
TrainingSample=xdata(Train,:);
TrainingLabel=group(Train,1);
svmStruct=svmtrain(TrainingSample,TrainingLabel,'showplot',true,'kernel_function');
title('Support Vector Machine for the prediction of pantograph interactions');
```

Figure A3.1 shows a scatter plot of two class, Class A pantograph events and Class B oscillation of contact wire after locomotive passed through the NS and excessive wind. The classification learner app is used to train and select the best classifier for the locomotive passes.

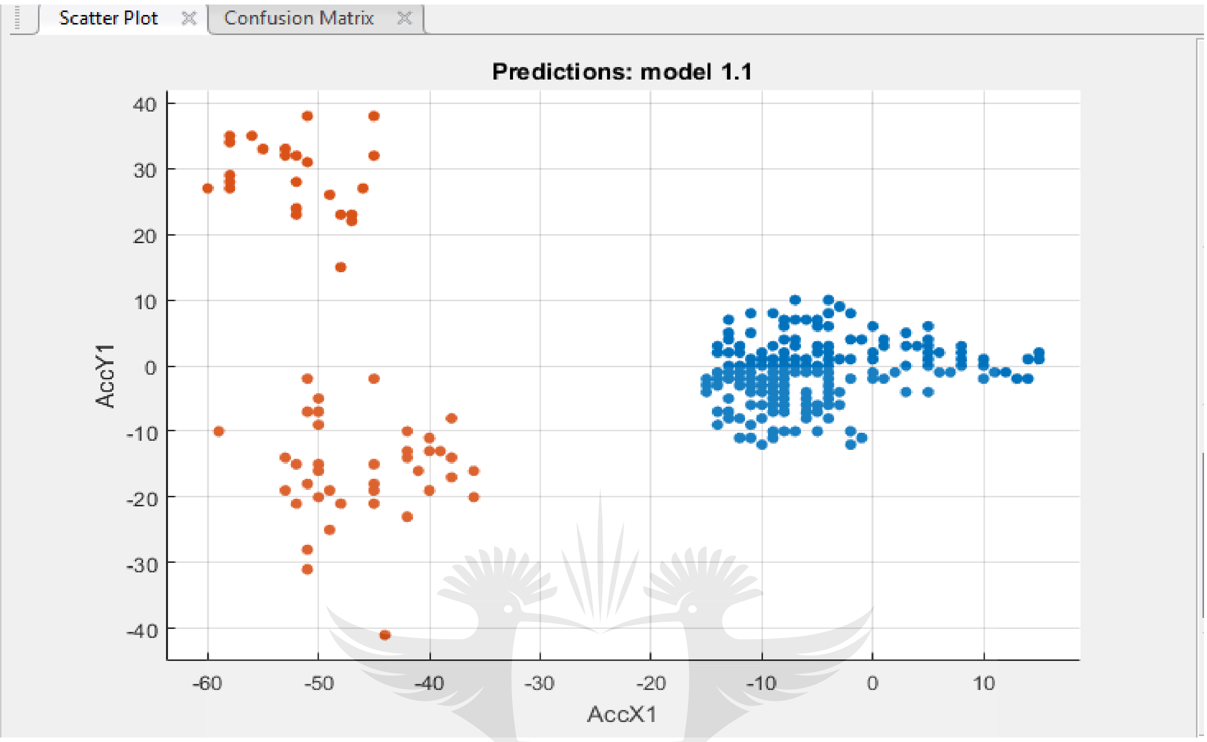

Figure A3. 1: SVM classifier for the prediction of locomotive interactions

Figure A3. 2 shows confusion matrix plot of 74 predicated classes and 356 events, the confusion matrix is used to assess the performance of the training model from the classification learner app. Figure A3. 3 shows the 100% true positive rate of the loco passes and events detected which means the classifier performance was able to predict the pantograph vibrations. The dominant diagonal with 100% indicates a good classifier (linear kernel SVM) since all the positive predicated values match the actual labels as shown on figure A3. 4.

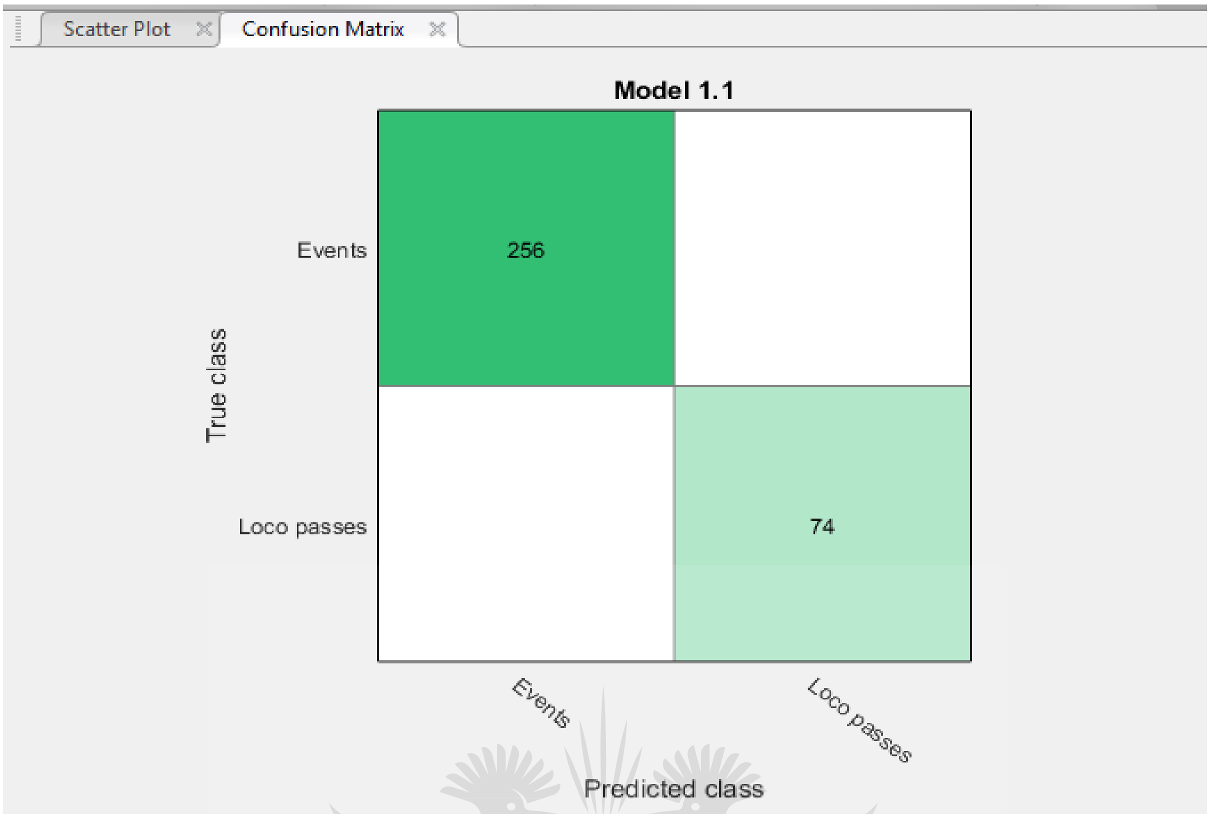

Figure A3. 2: Confusion matrix: Number of observations

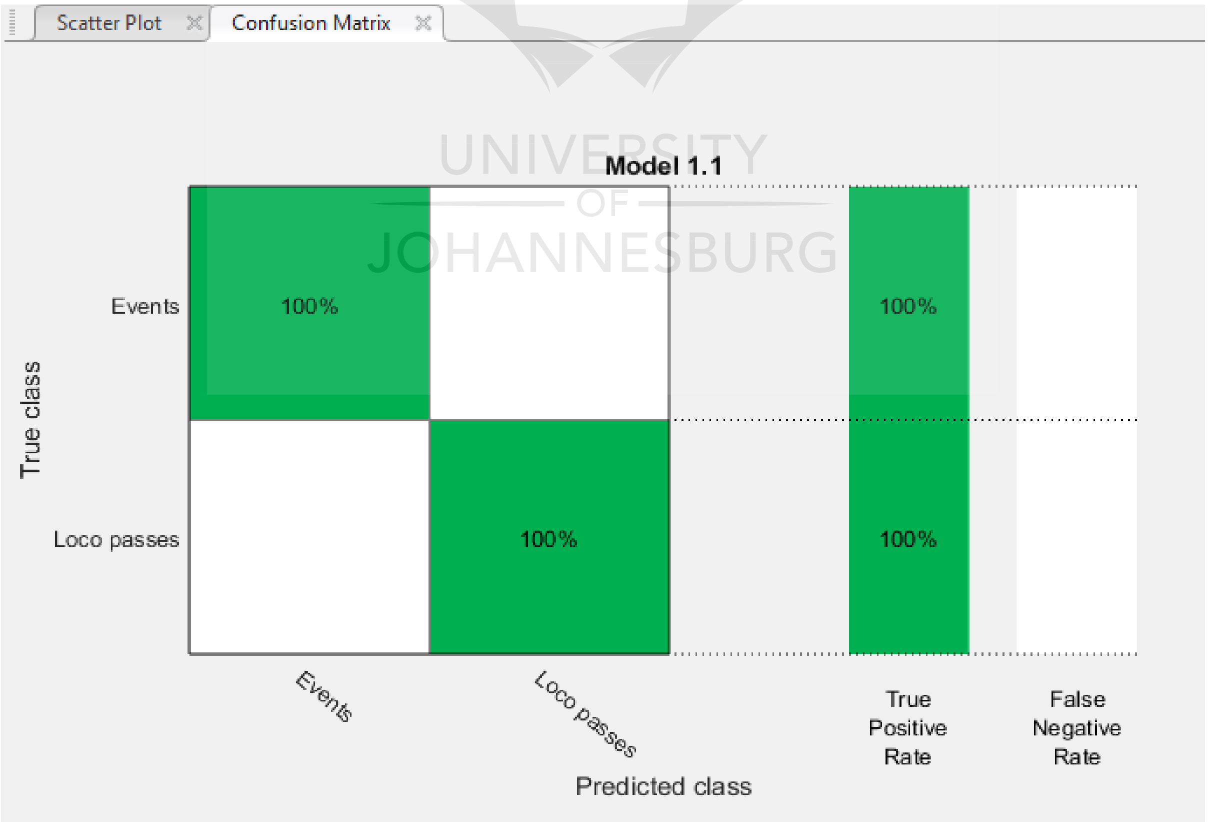

Figure A3. 3: Confusion matric: True positive rates vs False negative rates

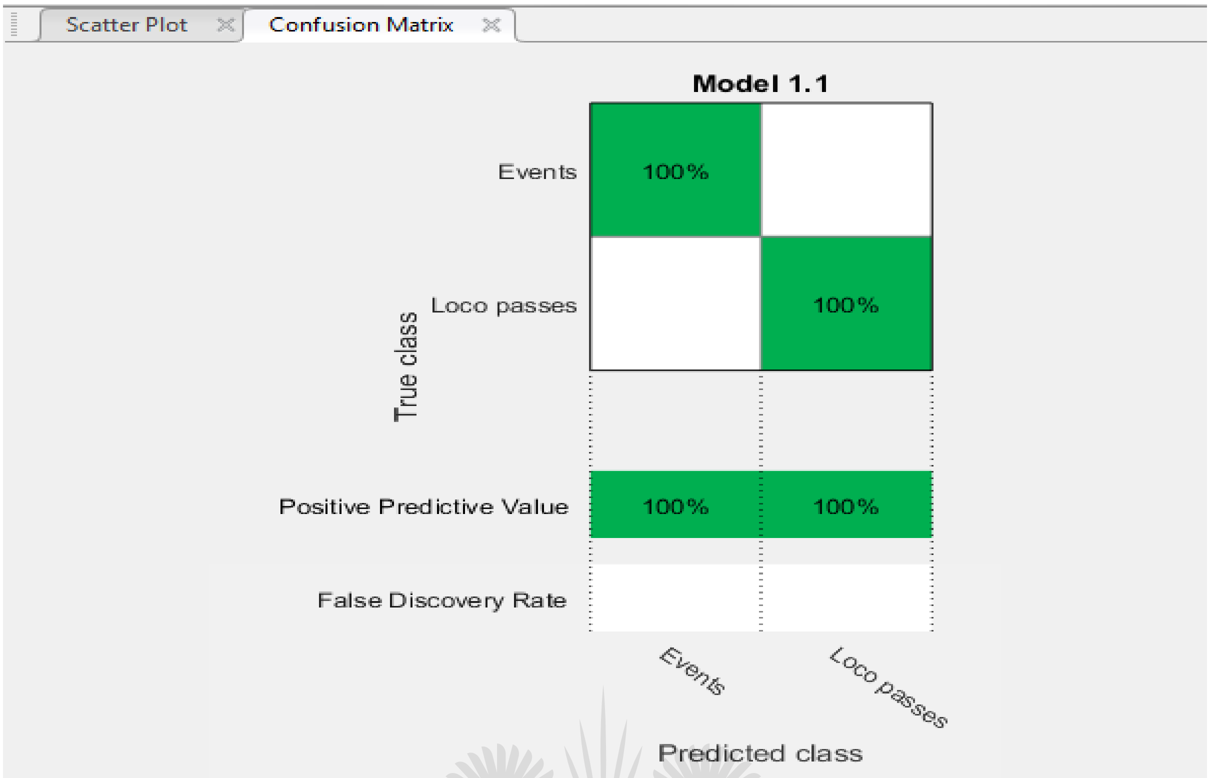

Figure A3. 4: Positive predicted vales versus False discovery rates

APPENDIX B: NEUTRAL SECTION HARDWARE

This appendix indicates the device components as explained in Chapter 3 and 4 used to detect and diagnosis failures. The device is installed on the NS using steel enclosure and parallel clamp 161/160mm² with modified copper bracket to hold the hold the enclosure firmly.

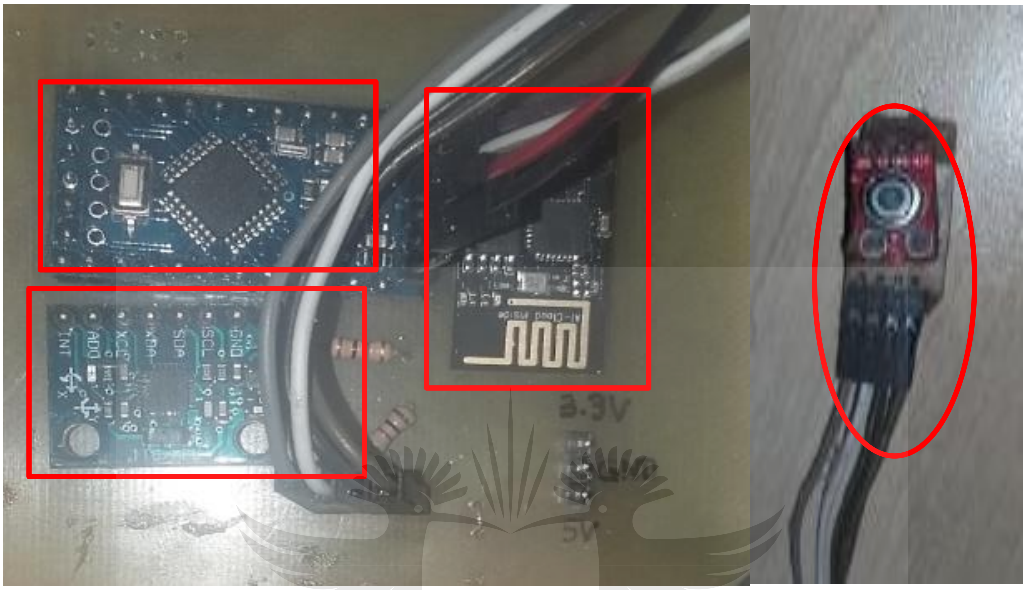

Figure B.1: Internal component of the hardware

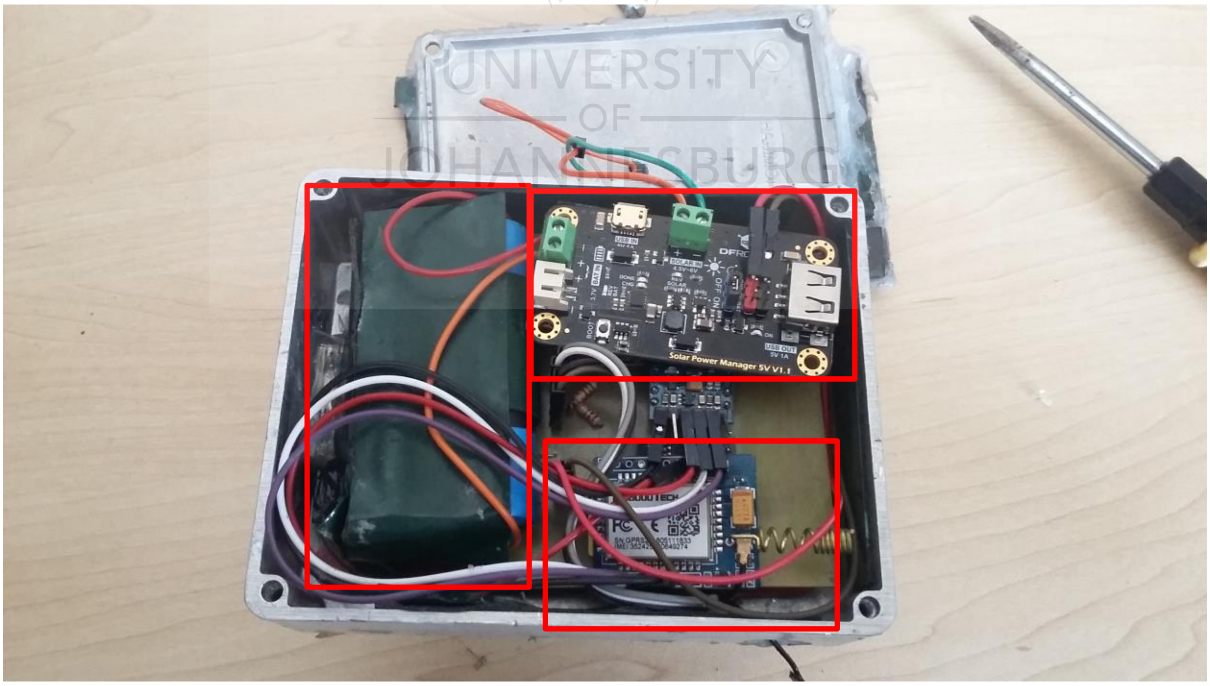

Figure B.2: Complete overview of the hardware for fault monitoring device

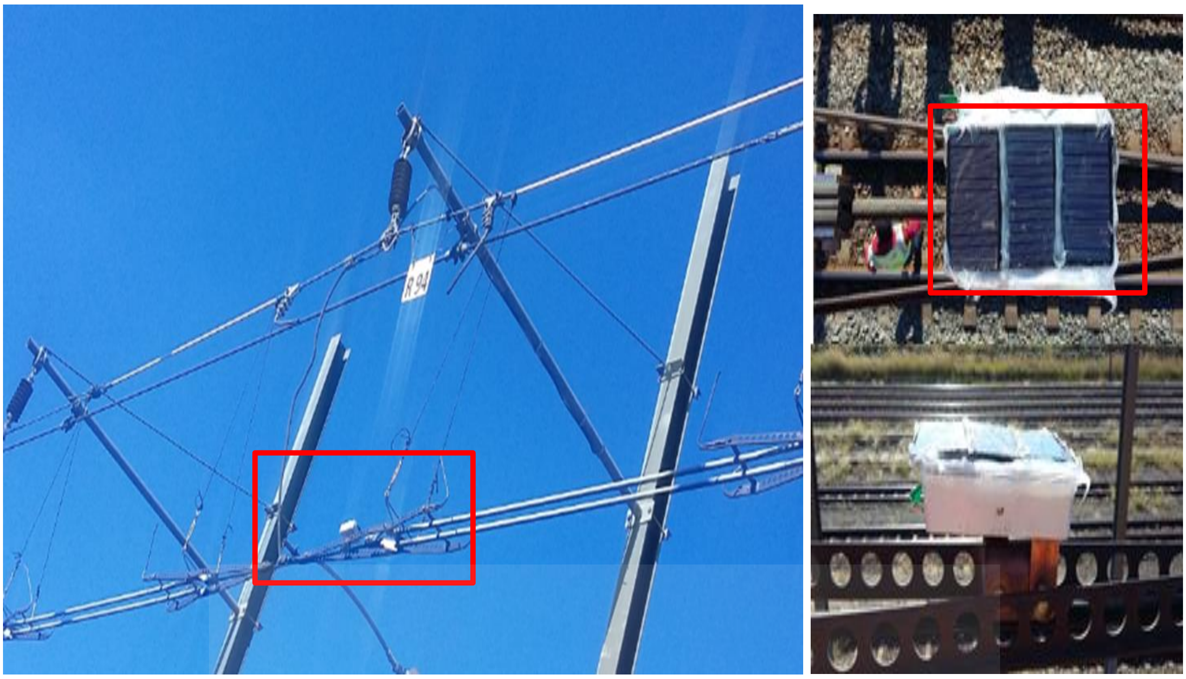

Figure B.3: Fault detecting device installed on the neutral section line number 1

List of hardware components used

1. Arduino Pro Mini
2. ESP8266 Wi-Fi module
3. ADXL345 accelerometer
4. Non-contact infrared thermometer sensor
5. 2x Lithium-ion batteries
6. Solar power manager embedded with MPPT
7. A6 gsm/gprs module
8. 3x 0.3W/5V Solar panels
9. Device installed on the NS for fault monitoring

Arduino Pro Mini technical specifications [92]

Microcontroller	Atmega328p – 8 BIT AVR controller
Operating Voltage	5V and 3.3V
Raw Voltage input	5V to 12V
Maximum current through each I/O pin	40mA
Maximum total current drawn from chip	200mA
Flash Memory	32KBytes
EEPROM	1KByte
Internal RAM	2Kbytes
Clock Frequency	3.3V --- 8Mhz 5V --- 16Mhz
Operating Temperature	-40°C to +105°C

APPENDIX C: LANGUAGE EDITING CERTIFICATE

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